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The impact of content on social media ads

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Résumé

L'étude de la publicité numérique à travers la relation entre le contenu publicitaire et le comportement des utilisateurs de médias sociaux constitue une entreprise précieuse dans le paysage marketing actuel. Pour prédire l'impact des trois dimensions du contenu - vente, social et qualité - sur l'engagement des utilisateurs de jeux sur les médias sociaux, cette recherche utilise une analyse qualitative moment-par-moment combinée à des données dérivées d'une campagne publicitaire réelle sur Meta. Les résultats démontrent que les dimensions du contenu ont un impact différent en fonction de l'engagement publicitaire, la qualité et la vente ayant un impact positif sur l'engagement publicitaire actif (clics), et le social ayant un impact positif sur l'engagement publicitaire passif (vues). En outre, cette thèse propose une approche méthodologique validée dans le contexte de la publicité sur les médias sociaux pour les jeux vidéo, qui peut être utilisée par d'autres études et entreprises.

Mots clés : marketing de contenu, engagement publicitaire, publicité numérique.

Méthodes de recherche : Recherche qualitative.

Abstract

Investigating digital advertising through the relation between ad content and social media users' behaviour constitutes a valuable endeavour in today's marketing landscape. To predict the impact of three content dimensions, *selling*, *social* and *quality*, on engagement of social media gaming advertising, this research employs a qualitative moment-to-moment analysis combined with data derived from a real-life advertising campaign on Meta. The results demonstrate that content dimensions have a different impact depending on the ad engagement, with *quality* and *selling* having a positive effect on active ad engagement (clicks), and *social* having a positive impact on passive ad engagement (views). Additionally, this dissertation presents a validated methodological approach for social media advertising in the context of video games, which other studies and companies can apply.

Keywords: content marketing, ad engagement, digital advertising.

Research methods: Qualitative research.

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KPIs: Key Performance Indicators

SNS: Social Network Sites

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Introduction

Among individuals aged 18 to 65 worldwide, it is becoming increasingly uncommon to find someone who has never been exposed to social media. Social Network Sites (SNSs) are at the core of many people's lives because of the inherent human desire to communicate and observe (Wilkinson & Thelwall, 2010), enabling users not only to receive information passively but also to participate actively, by sharing data, expressing opinions, and producing content (Wiese et Sanne, 2018). The widespread popularity of SNSs over the last few decades (Brossard, 2013) led to their monetization, upgrading them from communication mediums to also powerful sales channels (Kotler et al., 2017), with digital advertising featuring as the top promotional tactic (Statista, 2025) used by companies of all sizes.

However, being at the crossroads of humans' daily activities has diverse impacts. For example, the constant use of social media can lead to a sense of information overload (Zhang et al., 2020). Furthermore, when "a wealth of information creates a poverty of attention" (Davenport & Beck, 2001: 11), a concept known as attention economy, social media users dedicate less time when presented with purchase decisions (Nielson-Field, 2020), especially when they do not have strong buying intentions while scrolling their feeds on social media. Attention, then, becomes an important way for marketers to gauge consumer interest (Yang et al., 2020), impacting how brands execute advertising strategies nowadays. And one of marketers' resources to stand out on SNSs is their content strategy (Holliman & Rowley, 2014).

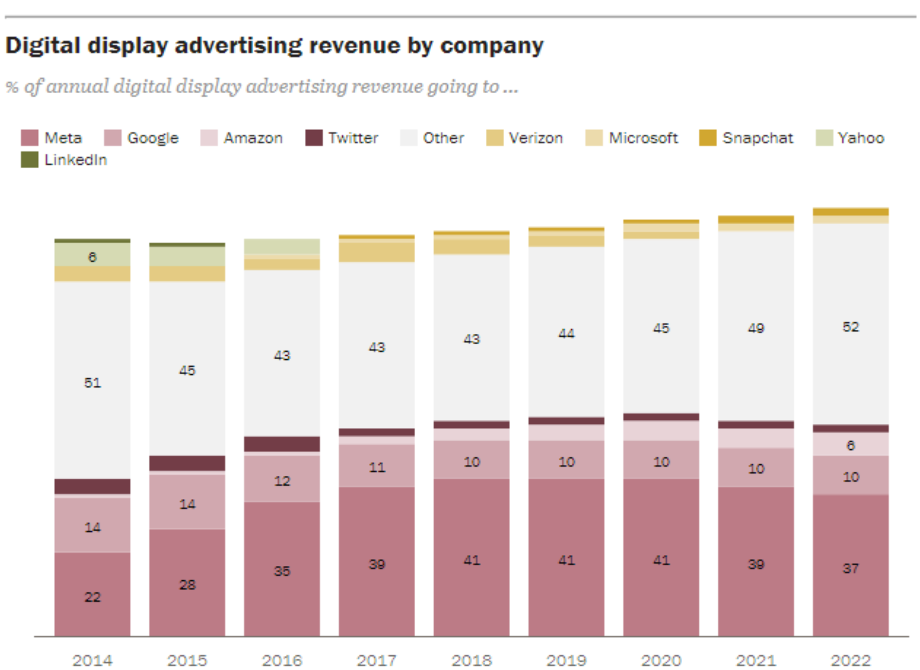
If companies want to generate business value (Culnan et al., 2010), they can start by crafting messages that spark positive actions on digital placements. Since in the digital advertising environment, brand communications' quality plays a crucial role in two ways: on the users' side, it catches attention, consequently taking space in consumers' minds (Sharp, 2010); and on the SNSs algorithms' (Bucher, 2012) side, it creates contextual relevancy, which will lead to increasing visibility in feeds.

Hence, investigating the effectiveness of advertising through the relationship between content and user behaviour becomes a valuable endeavour in today's marketing landscape, not only for managerial purposes but also for scientific (Wiese et al., 2020) investigations. Although, on the literature side, studying advertising through content is not a new topic, there are various ways to approach it, with a prominent framework attributed to Robert H. Ducoffe's works from the 1990s, which served as a departure point for this and other investigations (Arora & Agarwal, 2019; Fayyaz et al., 2023). However, as technology in this field continues to evolve, there is always a new lens through which this topic can be studied (Malthouse & Li, 2017).

Advertising on Meta

Evolving from TV and print, social media advertising is where most companies currently allocate media budget (Statista, 2025). This evolving market, with US$245 billion spent in 2022 in the US, the country with the most spending in advertising—growing from $221 billion in 2021 (Pew Research Center, 2023) — is dominated by a few tech enterprises. One of them is Meta, the mother company of Facebook and Instagram, which has steadily held one of the most significant shares of the display advertising market (Pew Research Center, 2023) in recent years, as presented in Figure 1.

Figure 1: Digital advertising revenue by company



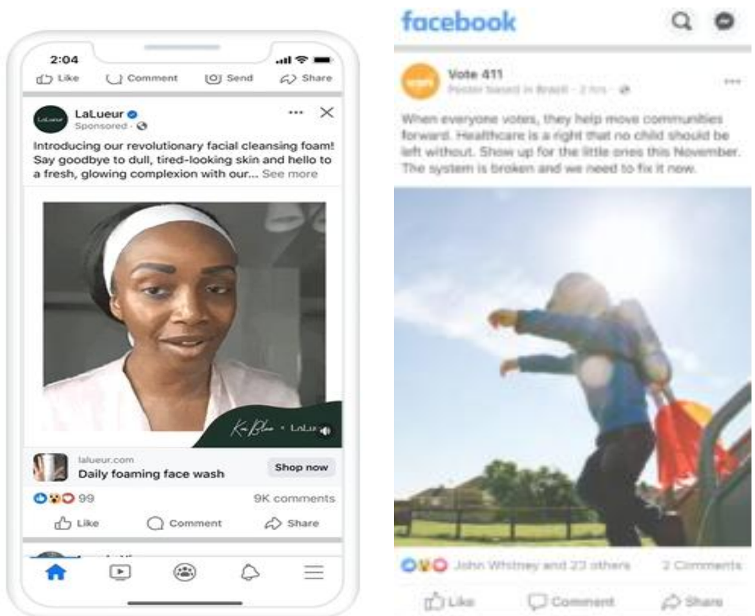
Source: Pew Research Center, 2023

Most companies shown in Figure 1 allow targeting the desired audience with efficiency, which is one of the reasons SNS advertising became so popular (Kim et al., 2019). Now marketers can choose socio-demographic attributes (Gender, Age, Location, Marital Status), Affinities (Gamers, Fans of Chocolate) and Remarketing (website visitors, converters), while receiving real-time reporting (Nielson-Field, 2020). However, on top of this, what makes Meta favoured for advertising spending is the public it consistently attracts.

Launched in 2004, Facebook Inc. was rebranded as Meta in 2021, with the mission to move social media toward immersive experiences (Facebook, 2021), such as augmented and virtual reality. Nonetheless, for the moment, Meta's revenue is primarily generated by ads, totalling over USD$131 billion in 2023 (Statista, 2024), coming from companies attracted to the access to Meta's active and growing user base. As The New York Times reported in 2023, approximately 3.14 billion people use at least one of the company's apps every day (Facebook, Instagram, WhatsApp, Messenger), representing a 7% increase from the previous year (Isaac, 2023). It is interesting to note that growth continues despite criticism of the company, including its involvement in a data breach linked to the political consultancy Cambridge Analytica, exposed in 2018 (McCallum, 2022), as well as the emergence of new SNSs, such as TikTok.

Except for the disclaimer "Sponsored", displayed at the top of a post, and sometimes a button with a call-to-action, advertisements do not significantly differ from organic content posted on Facebook and Instagram's feeds, where users arrive when launching the app or site, as illustrated in Figure 2. On the marketers' side, when starting a digital ad campaign on Meta, there are a multitude of decisions to be made: First, choose a campaign objective among the options awareness, traffic, engagement, leads, app promotion, and sales, which will guide the algorithm to find users who will perform the intended action (Facebook, 2024). Then, there are the budget, duration, target audiences, and the spaces where it will be shown (Feed, Stories, In-Video, Marketplace). Finally, on the ad level, there is a conversion location (website, app, Messenger, WhatsApp, Calls), a Call-To-Action (Book now, Learn more, Shop now, sign-up, Download), and the creative itself - with four formats (Video, Image, Carousel, and Collection) - which will portray the elements brand identification (Logo, Name), ad copy, creative (Video, Image), social aspects (Likes, Comments, Shares), headline, and Call-To-Action button (Facebook, 2024).

<u>Figure 2: A Sponsored Post (left) and an organic post (right) on Facebook</u>



Source: Facebook, 2024

While scrolling through the network, SNS users often see ads between pages they follow (or are suggested to follow) and friends' content. However, what is important in Meta's advertising is how users engage with the ad creative. As advertising money is being spent and impressions are distributed, advertisers receive real-time data about how users react to their creatives, which allows them to make improvements (Nielsen-Field, 2020). If well executed, these optimizations will lead to increased visibility and, ultimately, a higher chance of being chosen by a potential consumer.

Engagement on Meta

Compared to traditional media, social media advertising is more interactive with customers (Dewi et al., 2022), which changes the way ads are auctioned on these platforms. While monitoring what users read, click, and do, Meta's machine learning algorithm synthesizes the information collected and, in response, shows ads that match relevant themes to users (Wang, 2006). Then, it is up to the social media user to decide whether to engage with an ad (as they can also hide or ignore them by scrolling down). The more positive signals gathered from users, the more Meta will show the ad; thus, ad visibility works as a reward for advertisers (Bucher, 2012).

Then, in Meta's auction, a highly relevant element to improve ad engagement is the creative. Ads are assigned a value score (Facebook, 2024), which combines advertiser value (i.e., whether the brand is a good match for the desired target), estimated action towards the creative (based on the previous behaviour of targeted users), and ad quality, where marketers have the most influence. To determine advertising quality, Meta uses relevant metrics like quality and potential for engagement, which includes keeping the ad in the feed and then actively engaging (Shahbaznezhad et al., 2022) with it by clicking, commenting, sharing, or passively engaging (Pagani et al., 2011) with it, for example, watching a video. Therefore, by understanding the mechanics that involve content and engagement, marketers can strategize ways to outsmart the system and enhance visibility, as advertising perceived as high in value is more aligned with what customers want to see than what advertisers want to show (Ducoffe & Curlo, 2000). As a result, a high-value score on Meta will be a product derived from the message shown, which is in part content (Wiese & Sanne, 2018), but also its form, or how it is presented in terms of ad design (Pieters et al., 2010), with pacing, specifically fast-paced videos, attributed with generating higher ad engagement (Sundar & Kalyanaraman, 2004) on SNSs.

Gaming on Meta

Of all industries represented as advertisers on Meta, one stands out in particular: video games. According to Facebook's internal data, over 900 million users engage with games, watch gaming videos, or connect in gaming groups on Facebook each month (Facebook, 2021). So, it becomes relevant to focus this study on this economic sector that applies to a large portion of Meta users, providing suitable settings to test the association between advertising content and social media engagement. Second, as a medium visually rich in content (Atkinson & Parsayi, 2021), video games often use motion graphics to convey game narrative and design choices (Leino, 2012; Sicart, 2008), enticing potential players and laying a relevant foundation for investigating advertising content through its message and ad design. In conclusion, the considerable economic importance of this sector is worth noting. According to the report "Global Telecom and Entertainment & Media Outlook 2024–2028" from PwC (2024), despite a decline in the last couple of years, the gaming industry is expected to continue experiencing significant expansion, leading to potential growth in advertising spending. It is expected to reach over US$300 billion in annual revenue by 2028, which is double the 2019 figure (or pre-COVID years).

Research question

This dissertation seeks to understand the impact of content on social media gaming ads to assess the effect of advertising creatives on SNS engagement, allowing video game companies to enhance their ads, foster better interactions, and optimize their ad spend on Meta. And to achieve this broader scope, the present work draws inspiration from the methodological framework of Nepomuceno et al. (2020) while utilizing a qualitative moment-to-moment analysis (Baumgartner et al., 1997) of video advertising.

The proposed new perspective combines the qualitative analysis method with data derived from real-life paid digital media campaigns, differentiating this study by the fact that having access to this type of data is often a challenge (Malthouse & Li, 2017) for advertising research, which commonly relies on laboratory-created settings (Yıldız & Sever, 2021). The present dissertation was granted access to advertising reports from Meta Business Manager by a worldwide gaming company, allowing for the observation of SNS users' behaviour towards ads without scientific intervention (Grove & Fisk, 1992).

This company, which wishes to remain anonymous, shared the results of campaigns from Meta, where approximately 60% of their annual advertising budget is allocated. They provided reports, with data from 2022 to 2024, showing engagement metrics from potential clients of a mobile game, as well as their ad creatives, which, in approximately 90% of cases, according to this firm, comprise 30-second videos. Therefore, gaining more knowledge of how to improve engagement on videos on Meta would become a commercial advantage for them.

One of the managerial objectives of this research is to generate significant findings for gaming marketers to present advertising messages that are sufficiently compelling to capture the attention of social media users and increase mental availability (Sharp, 2010; Vaughan et al., 2020) by identifying the most effective combination of content dimensions for the anonymous video game. A theoretical goal is to propose a scientific method that other researchers can apply to enhance commercial performance through social media ads. Because Meta's family of Apps –the current leading SNS in terms of ad revenue and users– has an ad auction heavily impacted by the content of advertising and engagement, it becomes a perfect candidate for the medium of this investigation, which uses Views and Clicks deriving from social media ads to assess commercial performance. Within this context, an investigation of the moderator effect of one ad design choice, such as pace, was also included to enrich the analysis.

Therefore, based on the above framework, methodology, and objectives, the research question that guides the following pages is: In gaming advertisements on Meta, how do content dimensions *selling*, *quality*, and *social* impact ad engagement? The primary dependent variable in this project is *sustained views*, a passive type of ad engagement. However, as the investigation progressed, a need to include a secondary analysis, focusing on *clicks*, an active type of ad engagement, was observed and incorporated into the Results chapter to further knowledge, even if no hypotheses were initially planned for this construct.

The next chapter reviews the past literature on content dimensions and advertisement engagement. Then, the Methodology chapter details the study's design and method, including the criteria for ad selection and the coding process used for video content, which enables the moment-to-moment analysis in connection with data from real-life advertising. The results and key findings derived from the study are then presented, followed by a chapter that discusses these findings. The final chapter offers a conclusion, providing theoretical and managerial implications from the research and suggesting directions for future studies. Lastly, A.I. tools or software were not used in the preparation of this dissertation.

Chapter 1
Literature review

To examine the impact of content on social media gaming advertising, this research tests a phenomenon-driven model that identifies content dimensions in social media posts, using data collected from a real-life advertisement campaign of a confidential game on Meta (Facebook and Instagram). This section begins with the definition of key constructs, followed by the presentation of hypotheses, and concludes with the conceptual framework.

1.1 Ad engagement

Ad engagement can be described as the immersive, positive psychological state that fosters involvement and influences attitudes (Kim et al., 2017; Trabucchi et al., 2021). However, to develop a positive attitude toward a digital advertisement, factors like advertisement execution and consumer mood play significant roles, according to the “ABC model of attitudes”, originally formulated by Albert Ellis, who explored the Rational-Emotive behaviour subject since the mid-1950s, defending that “A” stands for activating events, “B” for beliefs about these events, and “C” for emotional and behavioral consequences of the beliefs (Ellis, 1991). Under a marketing lens, Solomon also highlighted Ellis’ concept in his work, presenting “A” as the way an object “affects” a consumer, “B” as the “behaviour” displayed, and “C” as the “cognition”, or the beliefs held by them (Solomon, 2011: 201). In essence, a potential client first needs to know, then feel, to ultimately engage. When materialized, an attitude towards a brand is viewed as a lasting assessment of the company, which, in consequence, will power behaviour (Spears & Singh, 2004), that can be positive or negative (Yousef et al., 2021). Negative attitudes may be driven by ads perceived as irritating (Ducoffe, 1996; Ducoffe & Curlo, 2000), which causes a decrease in response towards an advertisement over time (Li & Lo, 2014), something brands want to avoid.

On SNSs, engagement encompasses various attitudes toward digital advertisements (Wiese et al., 2020; Yousef et al., 2021), and, specifically on Meta, engagement can be measured by shares, reactions, comments, clicks, and views (Facebook, 2024). A positive action towards an ad (even the act of not hiding it) counts towards the advertisement quality equation that occurs inside Meta's advertising auction and leads to an increase in ad visibility, as the more positive attitude a creative collect, the more the algorithm will want to encourage this behaviour inside the platform (Wiese & Sanne, 2018). The other factor of the ad engagement equation, consumer behaviour, indicates that since attention is considered a “physiological measure of consumer engagement” (Yang et al., 2020: 4), grabbing SNS users' visual attention is an important achievement (Dallo, 2019) that will help drive potential clients through the cognitive process of perceiving and storing information (Li & Lo, 2014), facilitating learning and boosting ad effectiveness (Frade et al., 2022).

Considering the above and the fact that most of the data set provided by the anonymous gaming company consists of video advertising (about 90%), “views” becomes a suitable ad engagement metric among all advertising-related engagement types for the present investigation. It not only signifies the attention given by users but can also inform the duration of a view, indicating how engaged users were, since the amount of attention that viewers allocate to advertising changes as time passes (Frade et al., 2022), with the maximum level of effectiveness considered when an ad is viewed to its completion (Bellman et al., 2020), consequently, signaling to the algorithm positive behaviour that should be encouraged. Thus, Meta Business Manager helps marketers measure views with data related to the number of visual engagements an ad received at different stages: 3 seconds, 25%, 50%, 75%, 95%, and 100% of the video duration (Facebook, 2024).

Therefore, capturing a SNS user's attention and encouraging them to watch a video ad until the end is a valuable form of prolonged exposure, which will be referred to in this dissertation as *sustained views* and will be used as the primary type of advertisement engagement to answer the research question. Additionally, *sustained views* helps to bridge a gap between marketing literature and management since having access to the decay in views of a social media video ad by real SNS users—that was not produced in a laboratory for research (Yıldız & Sever, 2021)—can only be accessed by an advertiser via Meta Business Manager, as it is the case of this dissertation. This setting addresses a common challenge in digital advertising research (Malthouse & Li, 2017), which often relies on public ad engagements, such as likes, comments, and shares, visible on the feed to anyone. However, it is essential to note that advertisers cannot pinpoint which user account watched until the end; they only receive an aggregated total of views in reports.

Finally, since advertisements are "communications exchanges between advertisers and consumers" (Ducoffe & Curlo, 2000: 247), they will only form a positive consumer attitude if it is perceived by the viewers as high in content value (Arora & Agarwal, 2019; Ducoffe, 1996). On the contrary, advertising that lacks value tends to receive negative responses that brands want to avoid in the ad auction, such as being ignored, skipped, or even hidden. Therefore, the key to making users stop and stay longer with a video ad—and therefore, generate positive ad engagement — is tailoring the creative's content to the potential customer on social media.

1.2 Ad content

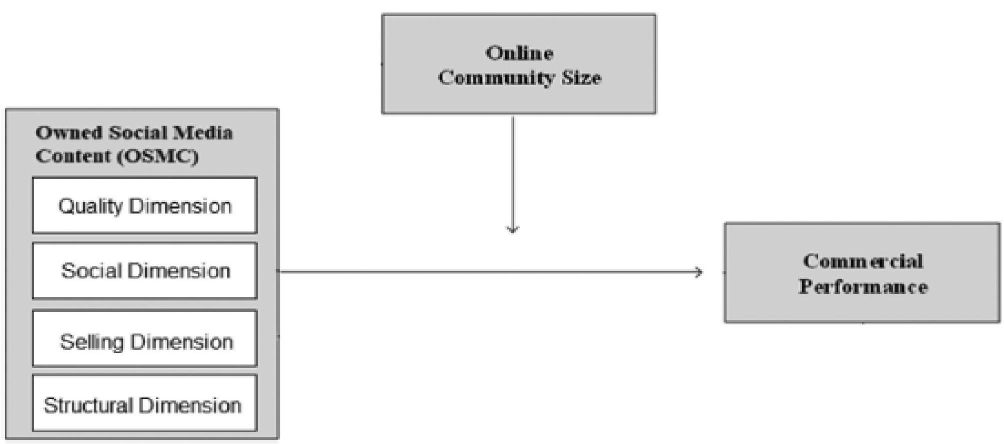
Content — encompassing words, images, or motion graphics — is a crucial element in conveying a brand's message (Holliman & Rowley, 2014). In the specific context of advertising, content is often analyzed under the lens of qualitative research, taking advantage of "Dimensionalization", defined as "identifying categories and exploring its attributes or characteristics along continua or dimensions" (Spiggle, 1994: 494), a substantive aid for theory construction, as it allows the analysis of constructs relationships.

In advertising literature, various dimensions have been proposed over the years to classify content. They could be based on a dichotomy, such as appeal (or strategy) versus the information transmitted (Ju-Pak, 1999) or emotional, based on imagery and emotions, versus rational, connected to facts and logic (Aaker & Norris, 1982). Previous researchers have also developed more comprehensive sets of dimensions, with the Resnik & Stern (1977) procedure being a notable example for analyzing commercials. This method, made for TV, but still employed in current studies (Ahmadi et al., 2022; Fulgoni & Lipsman, 2017), proposes 14 content dimensions in ads, namely Price, Quality, Performance, Components, Availability, Special Offers, Taste, Nutrition, Packaging, Warranties, Safety, Independent, Company, and New Ideas. The researchers explained that these content cues could be used in decision-making and presented the proportionality of ads considered informative. In the 70s, the most significant cues were components, performance, and price.

In other contemporary studies, analysing advertisements through comprehensive sets of content dimensions remains an evolving field. Dallo (2019), who was interested in analysing content marketing for gaming, used content dimensions to conduct a qualitative analysis of videos on the gaming social platform Twitch and found that social elements that portrayed a sentiment of community were a positive predictor of views of those long-form videos, which endorses the choice of views as the primary form of SNS advertising engagement to be explored in the present dissertation.

In another gaming-related study, Nepomuceno et al. (2020) employed a phenomenon-driven and qualitative approach to analyse Owned Social Media Content (content posted on social media feeds) from Facebook, Instagram, Twitch TV, and Twitter, aiming to understand commercial performance. Similar to Resnik & Stern (1977), the authors examined semantic units and categorised them into four content dimensions: structural, selling, social, and quality. Their findings indicate that commercial performance is higher with posts that highlight a product's value (quality) and those with an intent to sell (selling). Additionally, in mid-sized communities, posts intended to foster social interactions (social) tend to boost commercial performance, while the structure dimension did not have specific hypotheses. The conceptual framework used by Nepomuceno et al. (2020) is illustrated in Figure 3.

Figure 3: Nepomuceno et al. (2020)'s conceptual framework



Source: Nepomuceno et al., 2020

Therefore, based on Nepomuceno et al. (2020)'s work, which has successfully developed a methodology guiding knowledge on web content that leads to positive social media engagement in the gaming industry, the present dissertation will replicate their framework to analyse the content dimensions identified as statistically significant and positively linked to commercial performance: *selling, quality, social*. The new focus is to examine how these predictors influence ad engagement, specifically in terms of *sustained views*.

Finally, since the construct structure, defined as the type of content, including statics, live stream, audios, and videos, did not have a specific hypothesis in Nepomuceno et al. (2020)'s gaming study, the fourth dimension was excluded from the present analysis. Additionally, the data used in this dissertation comprised only videos, with the structure dimension consisting of only one type of content.

1.2.1 Selling dimension

Nepomuceno et al. (2020) define social media posts with a *selling* dimension as those that have a dominant commercial intent, which, in other words, means they promote an end goal to influence consumers, such as encouraging them to download a mobile game. When creating advertising messages, marketers use arguments to influence audience actions (Yousef et al., 2021), and these arguments can also be called key selling propositions, as they attribute value to a product or service (Strazewski, 2004) while trying to persuade with facts and logic (Aaker & Norris, 1982). Ads showcasing incentives, which can be considered rewards for potential clients (Fayaaz et al., 2023), include various monetary offers such as "free of charge," discounts, gifts, and coupons (Arora & Agarwal, 2019), as well as extending the product's lifespan through upsell and cross-promotion strategies (Kotler & Keller, 2000). An explicit intention to sell places the ad into a "direct selling" dimension (Nepomuceno et al., 2020: 1776), which may directly connect advertisements to purchasing cues, such as including a call-to-action and conveying urgency with words like "now."

However, marketing does not always need to propose a direct path to purchase, as it can be more subtle and utilize implicit selling intentions (Dallo, 2019). In this sense, advertising still shows incentives, but with an awareness-oriented objective. It serves as a precursor to achieving a purchase, as brand awareness can be defined as the likelihood that "a person retrieves a brand identifier and a product category needed from memory across brand-relevant situations" (Bergkvist & Taylor, 2022: 294). Therefore, ads that show a company's name and other identifiers are also part of the *selling* dimension, even if the selling elements are less explicit. In ads, brand awareness relies on strong brand identifiers, such as ad copy, sound elements, and visuals, like logos or colours (Colicev et al., 2018). These elements help build space in a consumer's mind and drive mental availability (Sharp, 2010; Vaughan et al., 2020), which means that once viewed by the desired audience, these identifiers will generate recognition, as selling elements have been found to influence purchase intention (Culnan et al., 2010). Furthermore, having potential consumers aware of a brand is highly correlated with consumers including the product in their purchase decisions (Laurent et al., 1995) and reducing ad recall from other brands (Alba & Chattopadhyay, 1986). Consequently, making an ad distinct becomes a big goal to bridge the gap between a brand and the consumer's memory in the attention economy (Nelson-Field, 2020).

In addition to implicit and explicit objectives, other related business objectives can be achieved through an advertising campaign. Marketers could try to sell the "ultimate version" or the latest "update" of the game to entice users who were on the fence about it with an additional selling proposition. Upselling is an effective sales technique that involves offering a more advanced or higher-priced version of a product (Denizci Guillet, 2020). Dallo (2019), while analyzing Twitch videos, also observed that videographers promoted subscriptions and in-game items as part of their sales approach. Another tactic, called cross-selling, refers to expanding the range of services a customer buys (Salazar, 2007), with merchandise and events among common examples in the gaming industry (Dallo, 2019).

Therefore, as selling elements facilitate an easy path for consumers to consider purchases (Nepomuceno et al., 2020), they can help foster a positive attitude towards an ad, translating into increased attention (Yang et al., 2020). This study predicts that video game ads featuring a *selling* dimension will positively interact with *sustained views*, and this is the proposed hypothesis.

- **H1:** The presence of the dimension selling is positively associated with sustained views.

1.2.2 Quality dimension

According to Ducoffe (1996: 22), advertising informativeness is "the ability of an ad to provide information for users to make a decision". Hence, the more information provided, the better the balance between consumers' needs and the brand's propositions (Arora & Agarwal, 2019; Resnik & Stern, 1977). In video game marketing, ads are often geared towards the functional sphere, such as car manufacturers' advertising, for example, making the level of advertising informativeness of these products entice potential consumers. However, they might not appeal to a non-gamer (or a non-truck enthusiast in the automotive sphere, for example), leading the ad to take an adverse turn to capture the attention of digital users in the social media context. Therefore, the information presented should be catered to the intended audience (Hamari & Sjöblom, 2017).

Providing insight into a product's quality with the right amount of information may reduce the risk associated with the need to search for more information, as literature suggests that a higher perception of quality is positively associated with purchase intentions (Moldovan et al., 2019; Tsiotsou, 2006). However, there is a fine line when communicating quality, as other studies have shown that users frequently exposed to excessive quality claims in advertising are less likely to perform an action that will lead to a positive commercial outcome (Kopalle et al., 2017).

In gaming, quality can be further utilized as gameplay, which "encompasses the challenges presented to the player, the actions made available to the player by the game designer to overcome the challenges and the interaction mechanism in the game" (Marshall et al., 2013: 82). Furthermore, gameplay can be broken down into functionality and aesthetics. Functionality encompasses game design choices and mechanics that illustrate how players interact with the rules and properties of the game (Sicart, 2008), including game goals, player actions, and strategies. At the same time, game aesthetics focuses on in-game tools related to appealing features (Leino, 2012). They are not part of the game's narrative, but they are important because they enhance the gaming experience through user choices. For example, they could be the sounds and colours of a car in a racing game or the weapon to be chosen in a first-person shooter. In ads, features are often promoted to entice potential buyers. Therefore, ideally, gaming marketers need to choose the arguments to persuade social media users not to "burn" their chances of success.

Accordingly, as quality elements strengthen consumer and brand identification (Nepomuceno et al., 2020), they lead to an increase in advertising perceived as high in value (Ducoffe & Curlo, 2000), which in turn enhances attention to the video ad. Therefore, this dissertation predicts that the *quality* dimension will have a positive impact on *sustained views*, with the following hypothesis:

- **H2:** The presence of the dimension quality is positively associated with sustained views.

1.2.3 Social dimension

In Nepomuceno et al. (2020), the social dimension was analyzed through posts designed to foster a sense of attachment with existing fans, a type of bonding, or to encourage fans to advocate for a game. The purpose of this type of content is to increase group cohesion and develop a sense of social community. Similarly, in Dallo (2019), this type of content was identified as the one set up by videographers to create an attachment with the individuals who have subscribed to their channel. The researcher identified many aspects within the social dimension: bonding, evangelization, defending, social spotlight, crowd-sourcing, and small talk.

User-generated content, especially influencer marketing, is becoming an increasingly popular tactic to enhance interaction in advertisements. Influencers can be described as online celebrities (Lou & Yuan, 2019) who create and share content on social media platforms. Influencer marketing then refers to content created by online creators who partner with brands (Hugh-Wilkie et al., 2022) to promote products/services to their followers. Considered “organic, authentic, and direct” (Lou & Yuan, 2019: 58), influencer marketing content has a strong potential to engage consumers, particularly when they endorse specific products. Additionally, a study termed “emotional contagion” (Solomon, 2011: 203) found that messages conveyed by happy individuals (featuring a smile) tend to boost positive attitudes towards a product.

Within the social sphere, the conversational tone of voice is also an important feature. Previous research has found that posts utilizing a human tone of voice, characterized by a more natural and informal tone (Barcelos et al., 2018), can have a positive or negative effect depending on the consumers’ context. Additionally, the use of interpellation, which involves addressing consumers directly using “you” in an ad, tends to enhance consumers' involvement (Cruz et al., 2017), ultimately creating engaging communication that intends to foster positive brand attitudes. Therefore, the social dimension adopts an emotional style (Aaker & Norris, 1982) when appealing to consumers, with influencers' trustworthiness being positively related to consumers' empathic responses (Jung & Im, 2021), which could influence passive types of engagement.

Consequently, because relationships motivate engagement in SNSs (Nepomuceno et al., 2020), and gamers are drawn to content that interacts with them (Dallo, 2019), the present study predicts that gaming ads on Meta containing *social* elements will positively influence *sustained views*. Therefore, this is the proposed hypothesis:

- **H3:** The presence of the dimension social is positively associated with sustained views.

1.3 Pace

In marketing on social media platforms, advertisements often reach consumers when they are not actively shopping or paying attention. However, for communication exchanges to be successful, a certain amount of attention from the receivers is required (Ducoffe & Curlo, 2000). That is when advertisement design choices (form), which are under the advertiser's control (Pieters et al., 2010), can enhance the impact of the content dimensions (message) on commercial performance. Pace, defined by Bolls et al. as "the number of visual cuts in an advertisement" (2003: 9), is one type of ad design intended to elevate arousal to a video. Originating from motion effects, this concept has been explored by researchers such as Sundar & Kalyanaraman (2004), who defend that humans tend to shift attention to the source of movement in a video.

As a video design choice, pace can be fast or slow, depending on the effect it wants to produce on the content presented on screen. To be fast-paced, a 30-second advertisement will display a minimum of 11 cuts (Yoon et al., 1999), and, in contrast, a slow-paced creative will show only 1 to 3 cuts throughout. Therefore, on average, a fast-paced ad will present one cut per 2.7 seconds, which would place the first disruption just before the 3-second mark if cuts are evenly distributed. Studies on fast-paced ads have shown that the increase in the rate at which information is presented forces viewers to process information more quickly and that it helps capture attention (Jin, 2016). In other words, "the greater the motion, the greater the arousal" (Sundar and Kalyanaraman, 2004: 15), and high arousal stimuli can contribute to prolonged advertisement views (Belanche et al., 2017). Therefore, as positive engagement in advertising involves attention (Geng et al., 2021) and an increase in engagement leads to improvement in message processing (Wang, 2006), ads taking advantage of many scene cuts (Yoon et al., 1999) and fast introduction of elements (Belanche et al., 2017), become an important element in the battle for consumers' attention on SNSs.

Still on the topic of ad design, besides introducing pace in a video, when crafting advertisements, marketers should also consider the moment they place new elements in videos, as research shows that effective information in commercials should be delivered within the first five seconds (Varan et al., 2020). On Meta advertising, specifically, the importance of the first seconds of the video ad is even shorter, at 3 seconds, as a Nielsen survey conducted in 2015 concluded that most advertising impact occurs at 3 seconds of the video, especially for ad recall and purchase intent (Facebook, 2015). Moreover, to assist advertisers, the SNS proposes a specific metric to measure attention at the start of the video called “Hook” (Facebook, 2024), which measures the number of 3-second video plays.

Now combining the construct *pace*, known for its impact on advertising attention (Bolls et al., 2003; Sundar & Kalyanaraman, 2004; Yoon et al., 1999), with the fact that the crucial moment in advertising on Meta is around the 3 seconds mark, this research proposes to introduce an exploratory variable comprising videos that display a cut, showing a change in scenery or a new element in the scene—a disruption in the first frame—within the first 3 seconds, which is a crucial moment to grab users’ attention on Meta, separating them from videos that have a linear, non-disruptive, start.

The goal of this exploratory variable is to understand, therefore, the moderator effect of this type of ad design working with the message, as adding *pace* early on the video advertising would moderate—change the relation (D’Astous, 2019)—between the content dimensions and sustained views. Finally, the hypotheses predict a positive moderator effect of *pace* on each content dimension, as previous research has found that embedding high-arousal stimuli in commercial spots increases consumer attention and promotes longer views (Belanche et al., 2017).

- **H4:** The presence of pace positively increases the association between selling and sustained views.
- **H5:** The presence of pace positively increases the association between quality and sustained views.
- **H6:** The presence of pace positively increases the association between social and sustained views.

1.4 Other variables

Besides content dimensions, pace and sustained views, there are other relevant metrics in Meta's advertisement environment worth being explored by marketers: Active Engagement, such as clicks, likes and comments, and Platforms, represented by Instagram and Facebook.

1.4.1 Clicks

Unlike *sustained views*, which are a passive type of social media engagement (Pagani et al., 2011), the act of clicking on ads can be considered an active form of engagement (Shahbaznezhad et al., 2022), with Meta defining an ad metric called "Clicks (All)" as the multiple clicks, taps, or swipes on an advertisement, including link clicks, post reactions, comments, shares, and other actions, such as liking a page (Facebook, 2024). Figure 4 exemplifies video ads on Facebook and Instagram (Facebook, 2024), showing the icons that represent the engagement metrics coming from Clicks (All) collected for this dissertation: link clicks are measured from the interactions with the button Shop Now; likes, shares and comments derive from clicking on the desired buttons on Facebook and icons on Instagram (heart, bubble and paper airplane).

<u>Figure 4: Example of an ad on Facebook (left) and Instagram (right)</u>

Source: Facebook, 2024

Literature in digital paid media indicates that clicking on an ad is a key indicator of advertisement effectiveness (Moran et al., 2019; Wiese et al., 2020) and that the higher the click rate (clicks relative to impressions), the more attracted consumers are to the ad (Wiese et al., 2020). However, more importantly, clicking takes users to the next step after advertising exposure, which is what firms desire (Cvijikj & Michahelles, 2013). This active engagement means that users feel compelled enough to act and, therefore, interrupt the passive viewing experience. Finally, in Nepomuceno et al. (2020), the authors used the sum of likes, shares, and comments to measure commercial performance. But in the present study, link clicks are also relevant because a call-to-action button is always displayed in the analysed ads.

It is also interesting to note that besides being an "active" form of engagement, Clicks (All) is also a mix of public or self-perceiving actions (Yoon et al., 2018) and private display of engagement, meaning it is possible to see the users that commented, shared or liked the posts. However, the number of clicks on the call-to-action button belongs to the advertiser. This also differentiates the variable clicks from views, which are a purely private form of engagement, as stated earlier in this chapter. Additionally, it is impossible to determine at which point the click occurred while a user was watching the video ad. Whereas with views, marketers have a richer set of data, as it is possible to know the decay in advertisement time watched within Meta Business Manager, giving it more relevance for time-related investigation (moment-to-moment analysis). Even though less valuable in the context of a moment-to-moment analysis, *clicks* are still a metric of high importance in Meta's advertising ecosystem and, therefore, were included in the investigation.

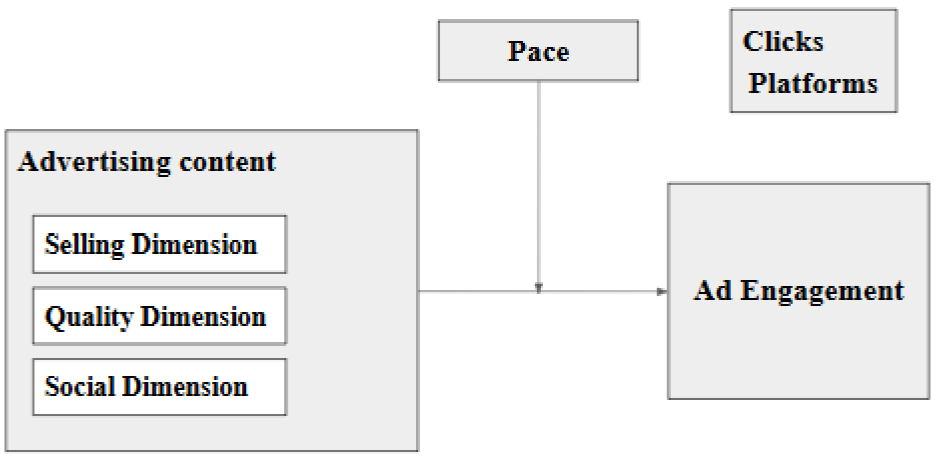
1.4.2 Platforms

An interesting factor related to social media advertising campaigns is the environment in which an ad is displayed or placed, which can significantly influence how the message is interpreted (Kotler, 1974; Shamdasani et al., 2001). When advertisers use Meta properties, they access inventory on two prominent social media platforms: Facebook and Instagram (Facebook, 2024). While the creative gathers engagements during an ad campaign, the impressions are optimised towards the platform where the creative receives more positive signals, as determined by Meta's algorithm. Therefore, two platform variables, *Facebook* and *Instagram*, which represent the advertising context and are also highly relevant to Meta's ad ecosystem, are included in the study.

1.5 Conceptual framework

As the current research aims to analyze the information cues within video game marketing that influence commercial performance, it becomes relevant to take inspiration from Nepomuceno et al. (2020)'s approach, bringing it to the context of social media gaming ads to address how the content dimensions *selling, quality* and *social* impact advertisement engagement, and if *pace* could moderate this relation. Therefore, the proposed conceptual framework is shown below.

Figure 5: Conceptual framework



As a conclusion, this project, based on formative measurement, in which causality goes from the indicators to the construct (Coltman et al., 2008), explores meaningful relationships between the content dimensions *social, selling, quality* (indicators) and ad engagement (construct), more specifically *sustained views*, while taking inspiration from past academic research developed to analyze the effects of gaming marketing content (Nepomuceno et al., 2020). Specifically for this context, clicks, platforms (Facebook, Instagram), and pace will also be part of the variables, aiming to ultimately determine which content dimensions of an advertisement can build a narrative that is compelling enough to bridge the attention barrier and generate higher ad engagement.

Chapter 2
Methodology

This research first employs qualitative research through a moment-to-moment analysis to identify the presence of content dimensions in videos used in digital advertising campaigns run on Meta between 2022 and 2024, which will be used as the independent variables. Then, it collects the real-life past data associated with online engagement generated by the ads, such as impressions, views and clicks, to investigate the impact of content on social media gaming ads, using statistical methods to uncover relationships between the different variables.

2.1 Choice of analysis method

As a substantial aid to explore how and why consumers behave (Belk et al., 2012), qualitative research was the departing point for this investigation via content analysis, a method that can be defined as “selecting a sample of communications and describing the communications through its form (number of words, presence of photography) or content (the arguments and themes used)” (D’Astous, 2019: 129). Particularly within the content analysis spectrum, this research employs a moment-to-moment analysis, a process used to test affective reactions to advertisements and overall ad judgments (Baumgartner et al., 1997), building from the approach proposed by Dallo (2019), who conducted a minute-by-minute observation of long form video of 30 minutes content on the platform Twitch, assessing the presence and absence of content dimension and sub-dimensions throughout each minute of the videos, without the help of a computer software.

For the present dissertation, the analysis using human observation, since it is the researcher who collects and records information on the content of each advertisement, breaks down 30-second videos into four blocks of time: 0s to 7.5s; 7.6s to 15s; 15.01s to 22.5s; 22.6s to 30s. Finally, the content of advertising videos is synthesized through a matrix representation, as it is a rigorous way to organize large sets of data for interpretation (D’Astous, 2019) and allows for transparency to enable readers to see the essentials of the collected data by the research.

Then, an indirect observational method is applied. This method, which seeks the preservation of the authenticity of the phenomena's natural state (Grove & Fisk, 1992), is employed because the present study relies on past data from a real-life advertising campaign provided by a gaming company (which wishes to remain anonymous) instead of recreating conditions in a laboratory, and, therefore, it collects data on user activities on Meta. Additionally, the researcher's absence at the time users watched the ads also helps lower the risk of bias, as literature indicates that the presence of a researcher can alter the audience's behaviour (Grove & Fisk, 1992). Once all data is collected and transformed, statistical methods are employed to identify patterns, trends, and relationships between different variables.

2.1.1 Study conditions

This research selected 133 videos shown on Facebook and Instagram, part of Meta's suite of apps, between 2022 and 2024, promoting a mobile game, including ten videos used for the pre-test. The requirements to enter the analysis were: videos (excluding static images and cinemagraphs) with a 30-second length (excluding videos of 15 seconds), and a minimum of 5,000 impressions. The number of impressions was arbitrarily chosen to ensure all ads had a minimum base of exposure on social media prior to the analysis and to minimize biased results from ads that received very low visibility.

The justification for videos as the only type of creatives stems from the desire to limit variations and confounding effects in data (Atinc et al., 2012). Plus, videos are considered the best source of encouraging content discovery (Moran et al., 2019), while 30 seconds is the standard ad duration, with half of all ads currently in circulation comprising this length (Barb, 2024). Longer duration advertisements increase learning and processing of ad information, according to the findings of Frade et al. (2022). On top of that, most of the dataset provided by the gaming company consists of 30-second videos.

2.2 Qualitative analysis

To ensure rigour in the moment-to-moment analysis, the content dimensions (*selling, social*, *quality*) were broken down into sub-dimensions. Following Dallo (2019)'s approach regarding the content of gaming videos derived from Twitch, the definitions of his 18 sub-dimensions belonging to the dimensions *selling, quality* and *social* were analyzed to classify them as relevant to the current gaming advertising context and not relevant – if specific to Twitch's environment – as shown in Tables 1, 2 and 3.

In summary, after reviewing the definitions proposed by Dallo (2019), sub-dimensions containing the following words were excluded: "channel/twitcher", "outside of the game", "events", "League of Legends", "other games", "community", "spectator/viewer". However, sub-dimensions related to the act of selling, the functionality of the game, and the goal of attracting new players were retained for the present research because they relate to advertising. Consequently, the following sub-dimensions were retained for the pre-test: explicit selling, implicit selling, in-game buyable, game mechanics & features, and evangelization.

Table 1: Dallo' Selling (2019) sub-dimensions and explanations

Dimension	**Sub-Dimensions**	**Dallo (2019)'s Explanation**	**Relevant**
Selling	Explicit selling	The content included any element explicitly intended to **sell** a good, service, subscription or derivative product.	Yes
	Implicit selling	The content included any element intended in an implicit, non-voluntary manner to **sell** a good, service, or derivative product.	Yes
	In-Game buyable	The content included information on **in-game** purchasable products.	Yes
	Subscriptions	The content included allusions to subscribing to the **channel**.	No
	Channel event	The content included material relating directly to the **channel**.	No
	Industry events	The content included elements linked to **events** around the game.	No
	Cross-promotion	The content included allusions to products and visual elements purchasable **outside of the game**.	No
	Product placement	The content included items relating to different products or items related to the game, but purchasable **outside of the game**.	No

Table 2: Dallo's Gaming (2019) sub-dimensions and explanations

Dimension	**Sub-Dimension**	**Dallo (2019)'s Explanation**	**Relevant**
Gaming	Game mechanisms & features	The content included elements relating to the different spheres of the **game or its mechanics**.	Yes
	Q&A (game)	The content included questions posed by the **"Twitcher"** or spectators on the subject of the game and its mechanics.	No
	Items descriptions	The content included references to any **League of Legends** item present in the game and its possible use.	No
	Bridging	The content included any allusion to **another game**.	No

Table 3: Dallo' Social (2019) sub-dimensions and explanations

Dimension	**Sub-Dimension**	**Dallo (2019)'s Explanation**	**Relevant**
Social	Bonding	The content includes any element that aims to create an attachment to the **viewer**.	No
	Evangelization	The content aims to be shared by as many people as possible or to **attract new players**.	Yes
	Defending	The content aims to defend the **community** and the game.	No
	Social Spotlight	Any content that aims to highlight a specific **viewer**.	No
	Crowdsourcing	The content included **community** support for the **channel.**	No
	Small talks	Content includes any element **not related to the game** that aims to create a dialogue with **spectators**.	No

2.2.1 Pre-test

A Pre-Test, considered a primordial method used by researchers to improve measurement instruments (D'Astous, 2019), was then applied in this study. The presence of content dimensions (*selling, quality, social*) and their sub-dimensions (explicit selling, implicit selling, in-game buyable, game mechanics & features, and evangelization) were analyzed in ten videos. The conclusion was that the three content dimensions could be used for the dissertation as they were present. However, some adaptation was required for the sub-dimensions. For its absence in the pre-test, "in-game buyable" was removed from sub-themes as it is not relevant within the material analyzed. It is believed that for this specific game, this is not an advantage promoted by their marketing team, as it is a free-to-play game, and including this content dimension would attribute the idea of using money to buy it. Furthermore, game mechanisms and features should be separated into two sub-themes, as gaming was the most prominent dimension in the pre-test, and the analysis could benefit from a more in-depth understanding of these content elements. Evangelization, as a social theme, was the content found least frequently in the ten videos randomly chosen for the pre-test; however, because it exists in the dataset, it was kept for the research.

2.2.2 Retained dimensions and sub-dimensions

In conclusion, this project retains the three main content dimensions *selling, quality*, and *social* initially proposed by Nepomuceno et al. (2020), and, additionally, adapts the sub-dimensions proposed by Dallo (2019) to conform with the reality of a free-to-play mobile game advertising sample of short 30 seconds videos aiming exclusively for new user's acquisition. *Explicit selling* and *implicit selling* form the two sub-dimensions of *selling*. At the same time, *game mechanics* and *game features* form the two sub-dimensions of *quality*. Finally, *social* has only one sub-dimension: evangelization. Table 4 shows the explanations and examples based on the data set of this dissertation.

Table 4: Retained sub-dimensions, explanation and examples

Theme	Sub-Themes	Explanation	Examples in the dataset
Selling	Explicit	Visual or audio with the aim of selling, with explicit **conversion** signals.	CTA: Text that denotes a call-to-action: Download, Play, Buy
	Implicit	Visual or audio with the aim to sell implicitly, with **awareness** signals.	Brand: Name of the game, Logo, Logo of the company
Quality	Mechanisms	Visual or audio related to the mechanics or "gameplay", with **choices made by the game developer**.	Functionality: Breaking, Accelerating, Overtaking, Road curve, Signage, Bumps.
	Features	Visual or audio related to in-game actions, with **choices made by the gamer** to enhance the experience.	Customizations: Difficult level, Color of the car, Brand of the car, City of the race.
Social	Evangelization	The content aims to attract new players, by featuring a **social element**.	Social: Humans, Voice, Emoji, Text directed at viewer that is that not the brand or CTA.

2.2.3 Moment-to-moment analysis

For the qualitative moment-to-moment analysis, to diminish cognitive bias – that is, when researchers use shortcuts to judge and decide quickly – a structured coding system is used to ensure consistent analysis across datasets and remove limitations (Crick, 2020; Paulus et al., 2024). To develop this framework, this dissertation adopts the framework used by Dallo (2019), who chose a binary collection method, with a 1 or 0 annotation: if the content creator (twitcher) used content from one of the coding themes during a minute, "1" was noted, and, if absent, "0" was added. In the same way, for this project, in each block grouped by an interval of 7.5 seconds (0-7.5s), (7.6s-15s), (15.01s-22.5s), (22.6s-30s), "1" was attributed to the presence and "0" to the absence of each sub-theme (Table 5) as visual or sound. Also, part of the moment-to-moment analysis, the moderator variable *pace*, is noted with the presence (1) or absence (0) of disruption within the first 3 seconds of the video, which signals that there is an increase in the speed at which information is presented with cuts or introduction of a new element in the first frame.

Table 5: Example of moment-to-moment analysis coding of one video:

Video 1 - Example		0-7.5s	7.5s-15s	15s-22.5s	22.5s-30s	**Total**
Selling	Explicit selling	0	0	0	0	**0**
	Implicit selling	1	1	1	0	**3**
Quality	Game mechanisms	1	0	0	1	**2**
	Game features	0	0	1	0	**1**
Social	Evangelization	1	0	0	0	**1**
Pace (Disruption 0-3 sec)		0				**0**

2.3 Secondary data

This research collected secondary data provided by a gaming company, which wishes to remain anonymous. They consented to the extraction of data from their Meta Business Manager, specifically from advertising campaigns that were live between 2022 and 2024. It is important to stress that this research does not interact directly with human participants, and to ensure lower risks for the company about information becoming public knowledge, data was encrypted and anonymized, with the inclusion of codes to campaigns and creatives so they cannot be identified. Furthermore, the gaming company agreed on the following measures: 1) After two years of publication, data collected should be destroyed; 2) Keep the game anonymous and do not reveal specific content that could identify the game or its characters; 3) Do not present images or videos from the game in the dissertation documents; 4) Only one person, the student, is allowed access to retrieve data.

The following past advertising data per qualified video from Meta Business Manager was collected: total impressions; impressions on Facebook; impressions on Instagram; number of views at 25% of the video; number of views at 100% of the video, and clicks (all), which consists of the sum of link clicks, shares, comments, likes.

2.4 Preparation of data for analysis

Once data was collected from the ads that passed the qualification phase (videos, 30 seconds, more than 5000 impressions), a final coding process was applied to facilitate the analysis and interpretation of the results using IBM SPSS software. The goal is to incorporate all the data: the independent variables (content dimensions) and other variables (views, pace, platforms, and clicks).

2.4.1 Independent variables

The independent variables used in this study are formed from the total sub-dimensions' presence (the sum of their presence or absence in four content blocks). After the moment-to-moment analysis was performed, for each video, the total presence of the five sub-dimensions (explicit, implicit, features, mechanisms, evangelization) is summed, their maximum can only be 4 - if they appear in all four blocks of time the video was divided –and a minimum of 0– if they do not appear.

However, it is important to note that the sub-dimension quantities are not equal in all content dimensions, since *social* only has one sub-dimension, while *selling* and *quality* feature two. Therefore, it's important to perform a transformation to give the same relative base, as Dallo (2019) was also required to do due to a different number of sub-dimensions in his work. Furthermore, that is why the sum of *selling* and *quality* must be divided by two in the calculations. In the example below (Table 6), Video 1's *selling* and *quality* dimensions variables are 1.5 (divided by two sub-dimensions), while *social* does not need to be divided, because it only has one sub-dimension.

Table 6: A representation of the content dimensions calculation:

<table>
<tr><td rowspan="3">Video 1 (Example from Table 5)</td><td>Sum of explicit selling Presence</td><td>Sum of implicit selling Presence</td><td>Selling dimension Total</td><td>Rationale</td></tr>
<tr><td>0</td><td>0</td><td>1.5</td><td>3+0 divided by 2 subdimensions</td></tr>
<tr><td>Sum of game mechanisms Presence</td><td>Sum of game features presence</td><td>Quality dimension total</td><td>Rationale</td></tr>
</table>

	2	1	1.5	2+1 divided by 2 subdimensions
	Sum of evangelization presence	**N/A**	**Social dimension total**	**Rationale**
	1	N/A	1	1 divided by 1 subdimension

Still on the topic of the independent variables, an interesting investigation is the moment at which the dimensions appear in the video and how they relate to a *sustained view*, in other words, to generate more extended engagement. For that reason, variables related to timing, as the start of the video (first 7.5 seconds) and the end of the video (22-second block), were also added to this study. The same logic of summing the presence of each sub-dimension was applied, but looking at only the first block of time in the "start" variables and the last block of time in the "end" variables, as Table 7 exemplifies. Therefore, in the end, there are six independent variables added to the initial *selling*, *quality* and *social*: Selling_7, Quality_7, Social_7, Selling_22, Quality_22, and Social_22.

Table 7: A representation of the start analysis calculation

Independent variable	Selling_7	Quality_7	Social_7
Presence (Based on Table 5)	0.5	0.5	1
Independent variable	Selling_22	Quality_22	Social_22
Presence (based on Table 5)	0	0.5	0

2.4.2 Other variables

For the variable related to *sustained views*, a views rate was created by dividing the percentage of users who reached a completed view (views at 100%) by the percentage at the start of the video (views at 25%). This metric intends to investigate if stronger videos (the ones with higher percentages) are leading social media users to stop scrolling and to consume the advertising content for a more extended period, which is an important form of engagement, and, therefore, a win in the battle for consumers' attention (Vaughn et al., 2020).

Table 8: A representation of the sustained view metric per video

	views at 25%	views at 100%	Sustained view rate (100% / 25%)
Video 1	500	100	0.2

For the variables related to active engagement, "clicks" is a rate created using data provided by Meta Business Manager: clicks (all) divided by impressions. Similarly, rates of Instagram impressions and Facebook impressions were based on all impressions. Finally, the moderator variable *pace* is a binary variable which collects 1 for the presence of disruption of pace within 3 seconds of the video and 0 for its absence.

2.4.3 Summary of variables used

Table 9 summarizes the variables selected for this study, along with their calculations. After all the transformations were made, data derived from each video were implemented into linear regressions in SPSS to understand how the dependent variable changes according to the content and, ultimately, address the research's objective: "What is the impact of content on social media gaming ads?"

Table 9: List of variables used in the study

Name of variable	**Calculation**
Implicit_presence	Sum of presence of implicit selling in the four blocks of the video.
Explicit_presence	Sum of presence of explicit selling in the four blocks of the video.
Features_presence	Sum of presence of feature in the four blocks of the video.
Mechanism_presence	Sum of presence of mechanism in the four blocks of the video.

Evangelization_presence	Sum of presence of Evangelization in the four blocks of the video.
Independent_Selling	Sum of presence of Explicit and presence of Implicit in a video, divided by two subthemes.
Independent_Quality	Sum of presence of Features and presence of Mechanisms in a video, divided by two subthemes.
Independent_Social	Sum of presence of Evangelization (only 1 subtheme)
Selling_7	Sum of presence of Explicit and Implicit in the first block of the video, divided by 2 subthemes.
Selling_22	Sum of presence of Explicit and Implicit in the last block of the video, divided by 2 subthemes.
Quality_7	Sum of presence of Feature and Mechanism in the first block of the video, divided by 2 subthemes.
Quality_22	Sum of presence of Feature and Mechanism in the last block of the video, divided by 2 subthemes.
Social_7	The presence of Evangelization in the first block of the video.
Social_22	The presence of Evangelization in the last block of the video.
Dependent_Sustained_view	Views at 100% level, divided by views at 25% of each video
Clicks	Sum of Clicks (All), divided by total impressions of each video.
Facebook	Impressions on Facebook, divided by all impressions
Instagram	Impressions on Instagram, divided by all impressions
Pace	1 for presence of disruption in video's pace within 3 seconds and 0 for absence.

Chapter 3
Results

After collecting data and conducting a moment-to-moment qualitative analysis of video ads from a real-life video game ads campaign, this chapter presents the findings of an investigation intended to measure the impact of content dimensions, *selling, quality*, and *social*, on *sustained views*, a passive form of ad engagement. However, as the investigation progressed, it became clear that *clicks*, an active form of engagement, had a great impact on the independent variables, and, therefore, a secondary model with this variable replacing views was included. Using the software IBM SPSS Statistics, the investigation includes description of the variables, their correlation matrix, followed by multiple linear regressions and moderation tests using Hayes PROCESS Macro and the metrics observed for results are R^2 coefficient, p-value, and standardized β.

3.1 Descriptive analysis

A descriptive analysis of the independent variables, shown in Table 11, was the first step of this investigation to better assess the coded data from the qualitative moment-to-moment analysis. It is noticeable that the most present content dimension is *quality*, with the highest mean (Mean = 2.476) of all three dimensions, followed by *social* (Mean = 1.62) and *selling* (Mean = 1.443). Now moving more in the details, a look at the Minimum and Maximum of the dataset signals the way the content was distributed throughout the four blocks the videos were divided into (1-7.5s, 7.6-15s, 15.1-22.5s, 22.6-30s): *quality* shows a maximum of 4, indicating there were videos in which both sub-dimensions, features and mechanisms, were present in all four timing blocks the ads were grouped for the qualitative analysis. *Social*, which only had one sub-dimension (*evangelization*), was also found throughout the video, as it received a maximum of 4. However, it is interesting to note that, in the selected data sample, beyond being the least used dimension, *selling* never had both subdimensions appear together throughout the video. Therefore, this discrepancy gives *selling* a maximum of 3.5 (the maximum concomitant appearance was 3 for subdimension *explicit selling* and 4 for *implicit selling*). As described in the methodology chapter, *selling* and *quality* dimensions have two sub-dimensions and are placed on the same relative base, since *social* has only one sub-dimension. Finally, a look at the standard deviation suggests that *social* has the highest variability among the three (SD = 1.818). Table 10 resumes the descriptive analysis of the content dimensions.

Table 10: Descriptive analysis of independent variables

Variables	N	Minimum	Maximum	Mean	Standard deviation
Selling	123	0	3.5	1.443	0.9413
Quality	123	0	4	2.476	0.8145
Social	123	0	4	1.62	1.818

Next, a histogram illustrates the frequency distribution of the independent variables in the videos within the four blocks of time (0-7.5s, 7.6-15s, 15.1-22.5s, 22.5-30s). The graphs reveal that *selling* (Figure 6) displays "2" as the highest frequency, indicating that more frequently selling elements are present two times among the four possible appearances, followed by "0", which notes complete absence in some videos. *Quality* (Figure 7) is primarily present between "2" and "3" times throughout the videos, explaining the highest mean (2.47). Meanwhile, *social* (Figure 8) has very high frequencies at "0", meaning total absence, and "4", observed throughout the video. Therefore, even though the means of *selling* (1.4) and *social* (1.6) were similar, their frequency of use in the videos differs: *selling* is mostly used 2 times, and *social* is either not used at all or used four times.

Figure 6: Histogram of selling

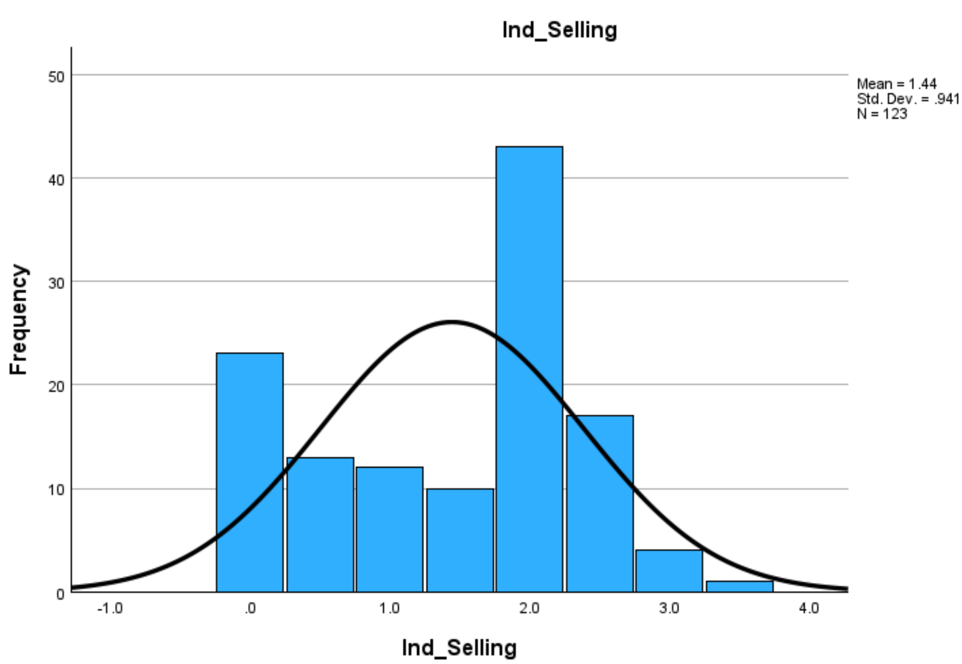


Figure 7: Histogram of quality

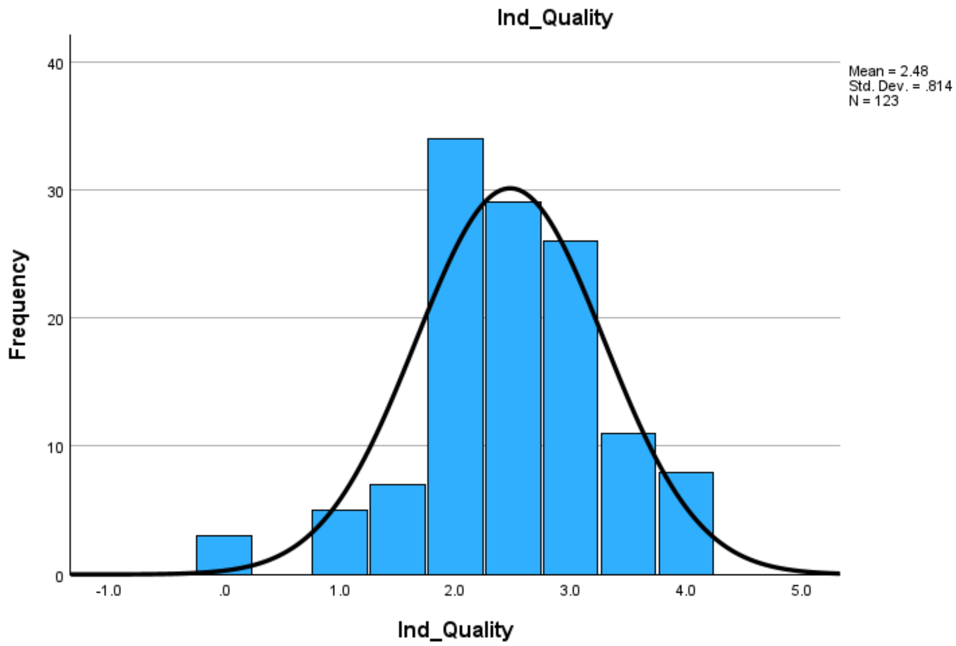
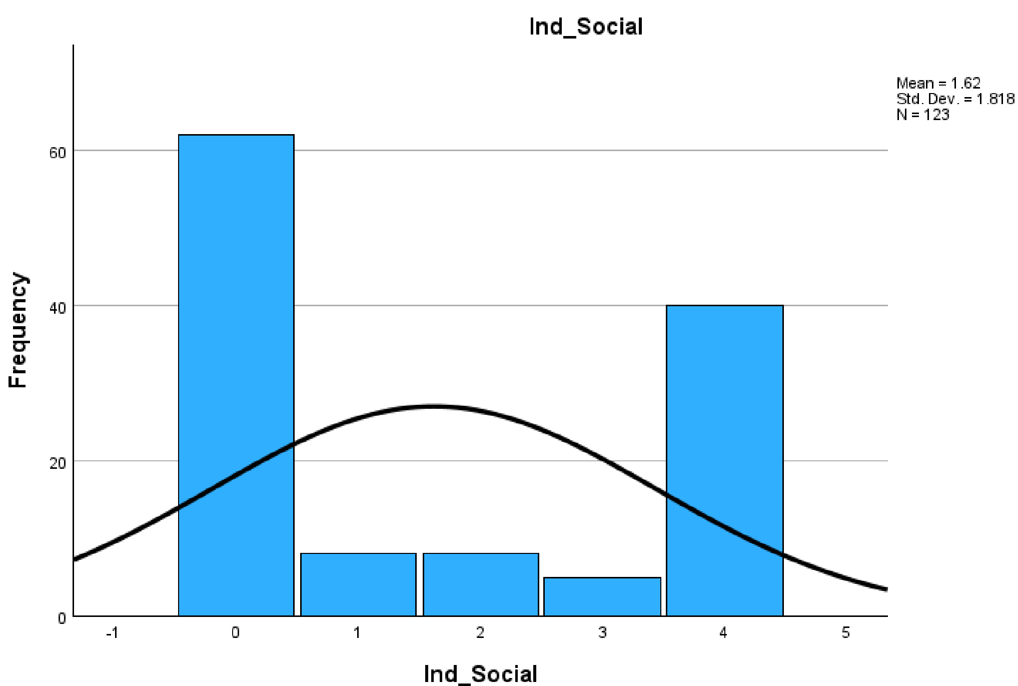


Figure 8: Histogram of social



Without missing and extreme values, the only transformation required was the standardization of these variables, as the Shapiro-Wilk test, used by statisticians to test for normality (González-Estrada & Cosmes, 2019), indicated that no content dimension followed a normal distribution, given that their significance level was lower than the 5% threshold.

Regarding the sub-dimensions that form the independent variables, a review of their frequency of use indicates that within the *selling* dimension, there is a high imbalance, with *implicit selling* (Mean = 2.36) having a four times higher presence than *explicit selling* (Mean = 0.53). Moreover, among *quality*'s subdimensions, weights are closer, even though *mechanisms* (Mean = 2.67) are more present than *features* (Mean = 2.28). *Social* only has one sub-dimension (Mean = 1.62).

Moving to the descriptive analysis of the collected data from past advertising campaigns associated with each video analyzed, the following table (Table 11) presents the other variables used in this study. It is worth noting a comparison between the two sites that represent *platforms*: Instagram's impressions rate has a higher mean than Facebook's (Mean = 0.58 vs. 0.41), which suggests that ads are more often served to users on Instagram than on Facebook. Furthermore, the mean of the *sustained views* shows that, on average, 22% of users who watched the first quarter of the video reached the end, as this variable is calculated by dividing 100% of the views by 25% of the views. This piece of data indicates that, on average, almost one quarter of users had a prolonged engagement with the ad, which confirms other studies that defend that social media users are often not "annoyed" by ads (Geng et al., 2022) and they consumed the content presented. Similarly, the click rate indicates that, on average, 1% of users who were served the ads clicked on them, hence actively engaging with the ad (stopped watching the video or scrolling their feed). At last, *pace*, which will be later used in the moderator tests, is present on average in 39% of the cases.

Table 11: Descriptive analysis of other variables used in the model

Variables	**N**	**Minimum**	**Maximum**	**Mean**	**Standard deviation**
Sustained Views	123	0.045	0.5737	0.2238	0.1088
Facebook	123	0	1	0.4118	0.2502
Instagram	123	0	1	0.5854	0.2604

Clicks	123	0.002	0.045	0.011	0.0072
Pace	123	0	1	0.39	0.2238

A Shapiro-Wilk normality test concluded that the variables sustained views, Facebook, clicks, and pace did not follow a normal distribution (threshold lower than 5%) and therefore they were standardized. The only exception was the variable Instagram.

The final step of this descriptive analysis was a correlation matrix (Table 12), which provided insight into the presence of covariance between many of the variables chosen for the present investigation, with asterisks indicating significant results.

Table 12: Correlation matrix

	1	2	3	4	5	6	7	8
1. Selling								
2. Quality	-0.71							
3. Social	0.071	-0.172*						
4. Views	-0.28	-0.145	0.248**					
5. Pace	0.057	-0.079	0.003	0.037				
6. Facebook	0.146	-0.066	0.035	0.416**	-0.068			
7. Instagram	-0.148	0.07	-0.034	-0.388**	0.095	-0.973**		
8. Clicks	0.156*	0.290**	-0.151*	-0.168*	-0.315**	-0.062	0.058	
* correlation is significant at 0.05 level								
**correlation is significant at 0.01 level								

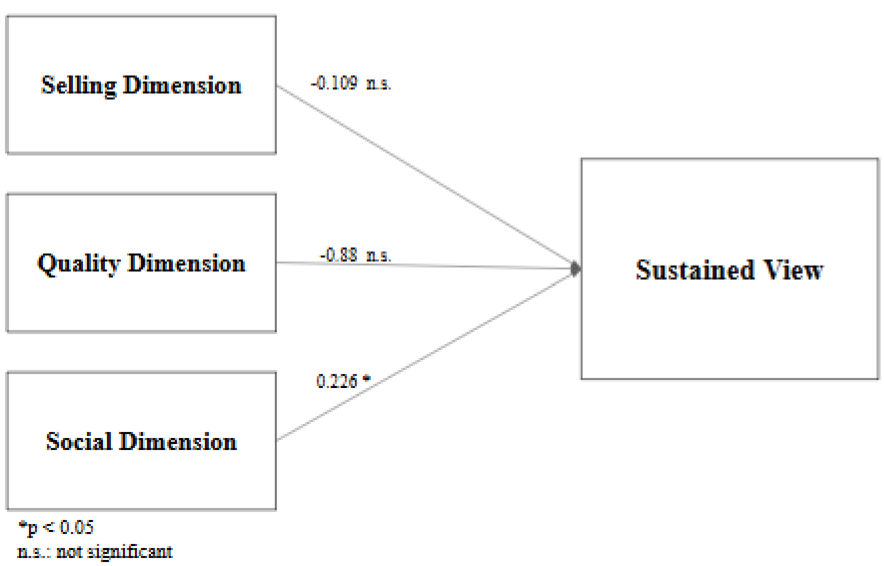
First, examining the independent variables, or content dimensions, *social* has a strong positive correlation with the variable *sustained views*, which aligns with the hypothesis of this dissertation, and exhibits a negative association with *clicks*. *Selling* was found to be positively correlated with *clicks*. *Quality* is also positively correlated with *clicks* but negatively correlated with *social*. Meanwhile, *sustained views* are positively correlated with Facebook but negatively with Instagram and *clicks*. Additionally, a negative correlation is observed between *pace* and *clicks*, as well as between *Facebook* and *Instagram*.

After noticing the importance of the variable *clicks* to this study, which was correlated with five out of seven variables in this model, notably the three independent variables (*selling, social* and *quality*, it was decided that: 1) Clicks would not be used as a control variable in the main model, because the descriptive analysis reveals it correlates with the three independent variables, therefore, being on the causal path between independent and dependent variables; 2) An additional model beyond the pre-established hypothesis, using clicks as the dependent variable, would be added to further knowledge on the relation of this variable with the content dimensions.

3.2 Sustained views analysis

To analyze the impact of content dimensions on *sustained views*, a multiple linear regression was performed (Appendix 1), using the independent variables *selling, social,* and *quality*, the dependent variable *sustained view*, and the control variable *platforms* (composed of *Instagram* and *Facebook's impression rate)*. Our predictors significantly explain *sustained views*, with the model being highly significant (p-value <0.001), and an R^2 of 25.1%. The main finding is that *social* is positively associated with *sustained views*, showing a statistically significant p-value (0.006) and the strongest association among the three content dimensions (β = +0.226). This result validates Hypothesis 3 (The dimension social is positively associated with sustained views), and the key results are shown in Figure 9. The other content dimensions did not yield statistically significant results and do not allow for the validation of H1 and H2 at this point in the investigation.

<u>Figure 9: Results of multiple linear regression with content dimensions</u>

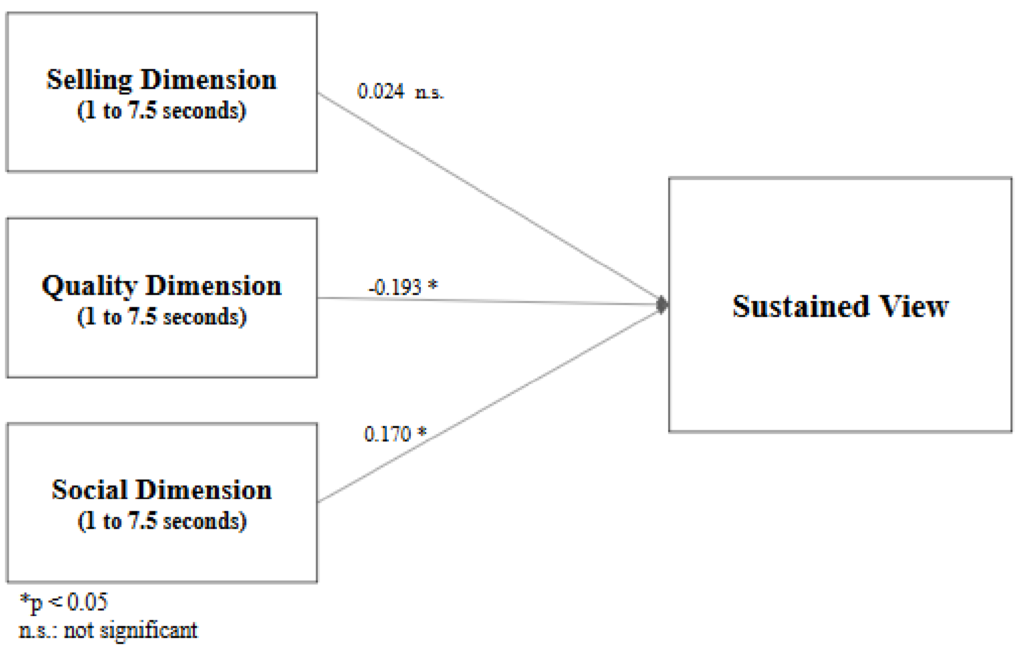


Nonetheless, the control variable *platforms* also provided findings: *Facebook* (based on Facebook's impression rate) is significant with *sustained views* (β= 0.711, p-value = 0.04). This is interesting because when comparing the means of both *platforms*, *Instagram*'s is higher than *Facebook*'s, which confirms that videos were shown less often in the latter. However, *sustained views* are higher on *Facebook*, whereas *Instagram* did not show significant results.

3.2.1 Start of the video analysis

It is also valuable to investigate how the content dimensions displayed at the start of the video, as well as at the end, could work as predictors of the dependent variable, which is based on timing, being the ratio of users who finished the video (last 7.5s) divided by those who started (first 7.5s). To investigate the start of the video, a multiple linear regression was performed (Appendix 2), using independent variables Selling_7, Social_7, and Quality_7, which indicate the presence of the content dimensions in the first 7.5 seconds of the video (or the first 25% of the total 30 seconds).

<u>Figure 10: Results of multiple linear regression with content dimensions - at start</u>

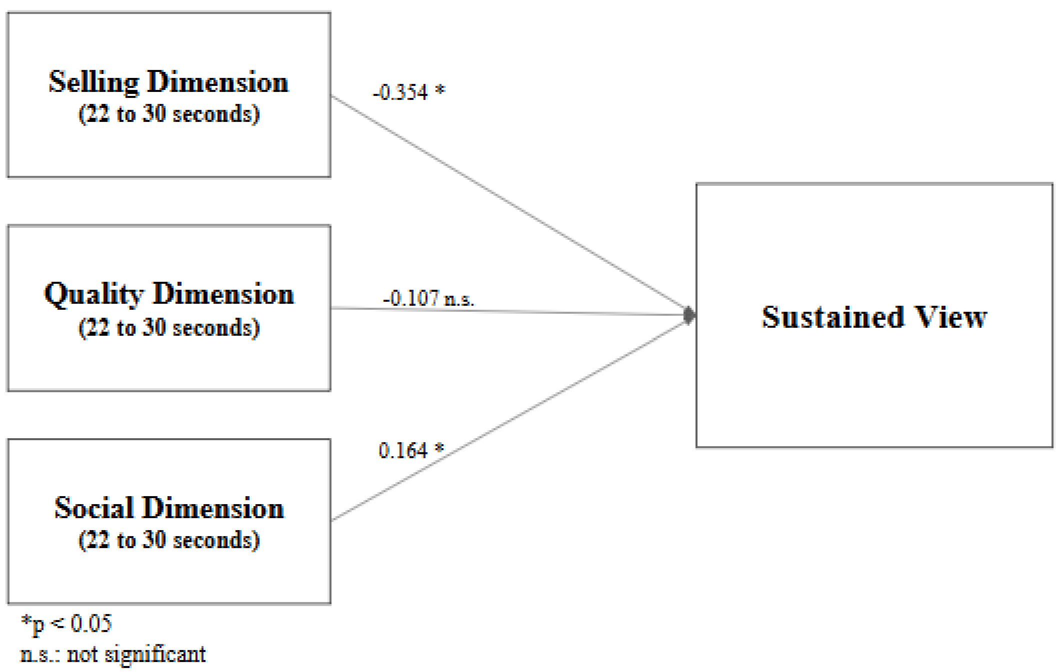


As the model in Figure 10 shows, the predictors significantly explain *sustained views*, with a highly significant p-value (<0.001) and an R^2 of 26.4%, which is higher than the model based on the entirety of the video (R^2 of 25.1%). The "Start of the Video" analysis reveals that *quality*'s association with *sustained views* becomes statistically significant, but with a negative Beta (β = -0.193, p-value = 0.023). *Social* remains a significant positive predictor in the second model (β = 0.170, p-value = 0.044). Still, it is interesting to note that the Beta coefficient becomes weaker than in the original model in section 3.2 (+0.226 versus +0.170). Moreover, on the control variable *platforms*, Facebook's positive strength is the highest among the significant βs (β= 0.698, p-value = 0.044), whereas Instagram remains insignificant.

3.2.2 End of the video analysis

The same idea was applied to investigate the end of the video with a multiple linear regression (Appendix 3), using as independent variables Selling_22, Social_22, Quality_22, which indicate the presence of the content dimensions only in the last 7.5 seconds of the video (or the final 25% of the total 30 seconds), as demonstrated in the following model (Figure 11).

Figure 11: Results of multiple linear regression with content dimensions - at end



The predictors significantly explain *sustained views* with the model being highly significant (p-value < 0.001) and R^2 of 30.8%, which is more prominent than the model based on the entirety of the video (R^2 = 25.1%) and the one at the first 7 seconds (R^2 = 26.4%). The end of the video analysis allows to conclude that *social* at the end of the video is a significant positive predictor of *sustained views* (β= 0.164, p-value = 0.03), and, on the other direction, that *selling* at the end of video is a significant negative predictor of *sustained views* (β= -0.354, p-value = 0.001).

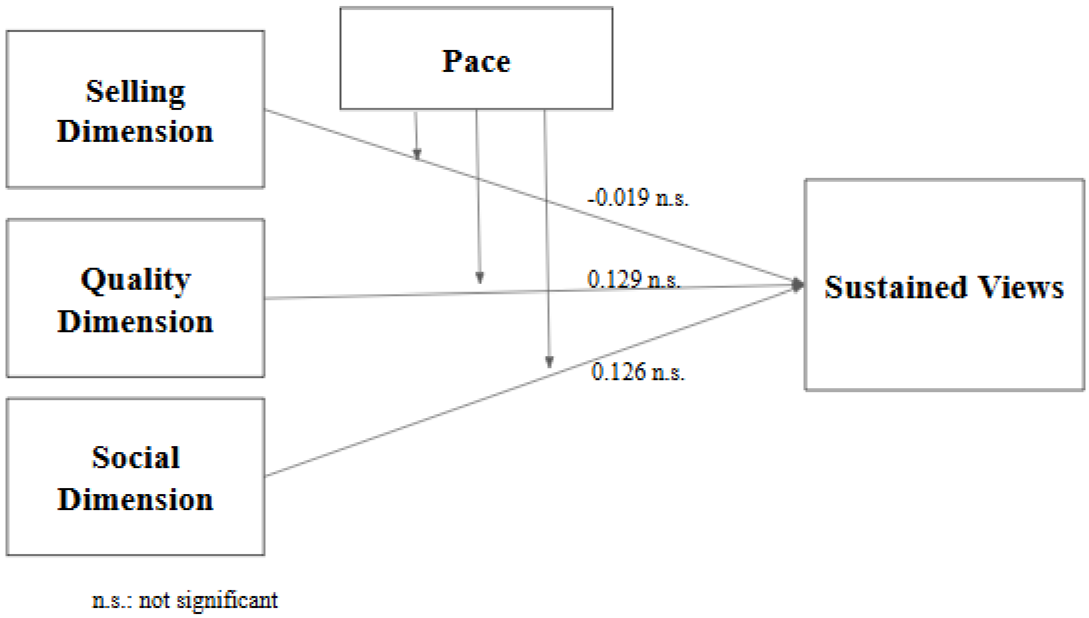
In summary, these results show that the models predict that including *quality* at the start of the video generates a significant negative association with *sustained views*. Meanwhile, at the end of the video, adding *selling* elements generates a significant negative association with prolonged views. Both results, now significant, go in the opposite direction of hypotheses 1 and 2, which evaluated a positive relation between variables. However, including *social* produces a significant positive association at the start and the end of the videos, which helps further solidify the acceptance of hypothesis 3.

3.3 Moderation test

In the moment-to-moment analysis, the presence and absence of *pace*, observed as a disruption in the video's first three seconds of the ads, in the form of a frame cut or new element introduction, was a data point collected. The objective is to understand if it positively influences the association between content and extended ad engagement, as it is artistically intended to attract viewers' attention (Jin, 2016) while scrolling their social media feeds. To investigate the moderation effect, regressions using Hayes PROCESS Macro in SPSS were performed with *sustained views* as the dependent variable, plus *selling*, *quality*, and *social* as independent variables, *pace* as the moderator, and *platforms* as the control variable. Three regressions were created, each featuring one interaction term (*selling x pace, quality x pace, social x pace*). The results (Appendix 4) are summarized in Figure 12.

The moderator tests show that the interaction effect of Pace is not statistically significant with any content dimension; therefore, H4, H5, and H6 are not supported. Although the effect is not statistically significant, it is still interesting to examine the direction of the effect (β) on *sustained views* in this section. The hypotheses were all positive, meaning the association would be stronger with the moderator effect. However, there is a potential indication, which unfortunately cannot be confirmed, that the results would be positive with *quality* (β = 0.129) and *social* (β = 0.126) when the interaction with *pace* is included as a moderator. Although inconclusive due to the lack of significance levels in the moderator test, these results suggest that there is room for further investigation into the effects of *pace* and content dimensions in future studies.

Figure 12: Summary of results of moderation test with views

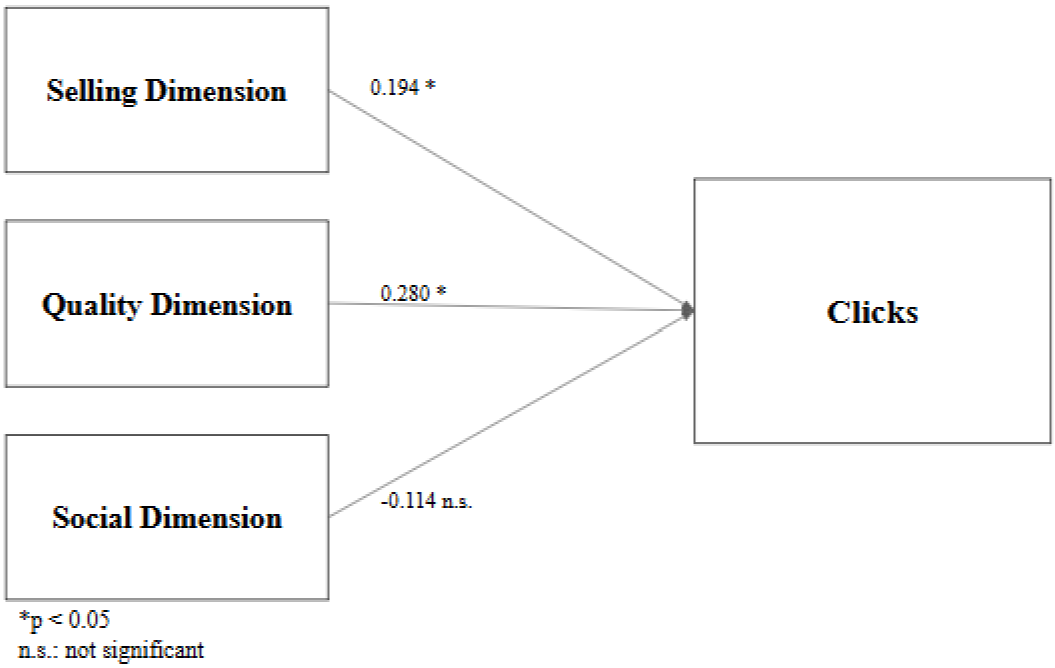


3.4 Clicks analysis

Initially, in this dissertation, *clicks*, which represent the click rate (a ratio of the number of all clicks divided by the total impressions each ad received), were chosen as one of the control variables due to their importance in conveying consumer interest signals (Wiese et al., 2020). However, to further analyze this variable found to be positively correlated with *social, selling* and *quality* in the correlation matrix (Section 3.1), an additional investigation was conducted using clicks as the dependent variable and replicating the same variables used in the principal regression with *sustained views* (Section 3.2) for comparison, having only *platforms* as control variables. Even though a hypothesis was not initially formulated for it, using *clicks* is a relevant form of ad engagement, consistent with past research on advertising message effects, which proposes that having a potential consumer engage with an ad, like clicking on it, forms the foundation of consumer brand selection in response to marketing communications (Wang, 2006).

The results (Appendix 5) of the multiple linear regression show that this second model also has significant explanatory power ($p < 0.001$), with R^2 of 13.3%, which is weaker than the first model with *sustained views* as the dependent variable, which features R^2 of 25.1%. Figure 13 illustrates the key interaction results.

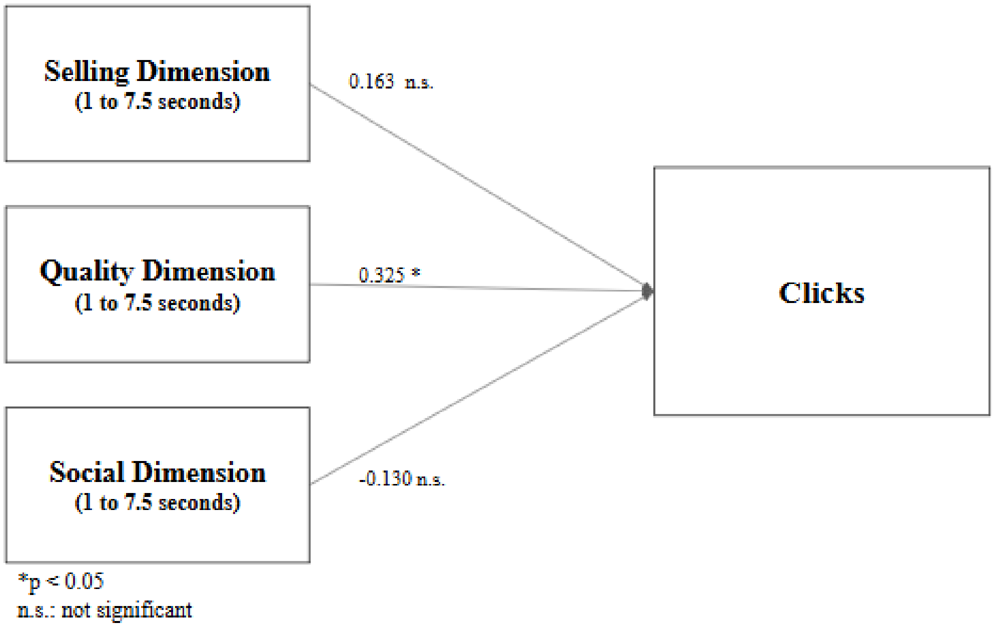
Figure 13: Results of multiple linear regression with content dimensions and clicks



Following the same structure, by including *platforms* as the control variable, and the content dimensions as independent variables, now *clicks* is the dependent variable. The second model reveals that, among the statistically significant results, two content dimensions work as significant positive predictors: *quality* (β = 0.280, p-value = 0.002) and *selling* (β = 0.194, p-value = 0.028). It is worth noting, though, that in this model, neither platform (Facebook nor Instagram) nor *social* has a significant association with clicks.

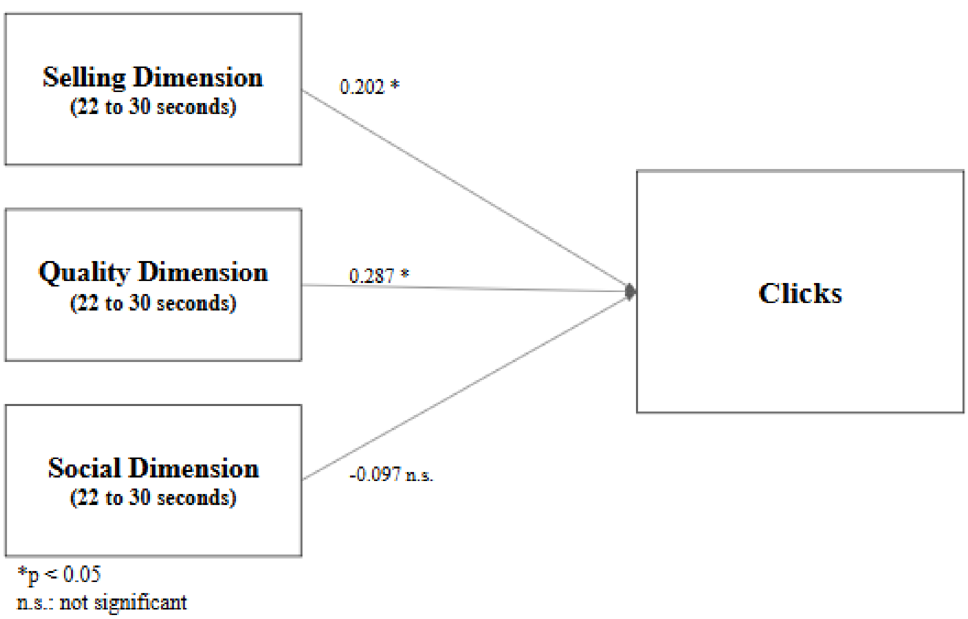
Moving forward, for comparison with the results of *sustained views* as the dependent variable, the start and end analysis was also replicated using *clicks*, this time as the dependent variable. At the start of the video (first 7.5 seconds), among the statistically significant results, *quality* is positively associated (β= 0.325, p-value = 0.001), while *selling* has a borderline significant association (β= 0.163, p-value = 0.054), as shown in Appendix 6, and demonstrated in Figure 14

<u>Figure 14: Results of multiple linear regression with content and clicks - at start</u>



At the end of the video (the last 7.5 seconds), the positive effect of *selling* becomes statistically significant (β = 0.202, p-value = 0.035) and *quality* remains positively associated (β = 0.287, p-value = 0.003), as shown in Appendix 7. The decrease in the association strength between *quality* and *clicks* as the video progresses is also notable (β goes from 0.325 to 0.287).

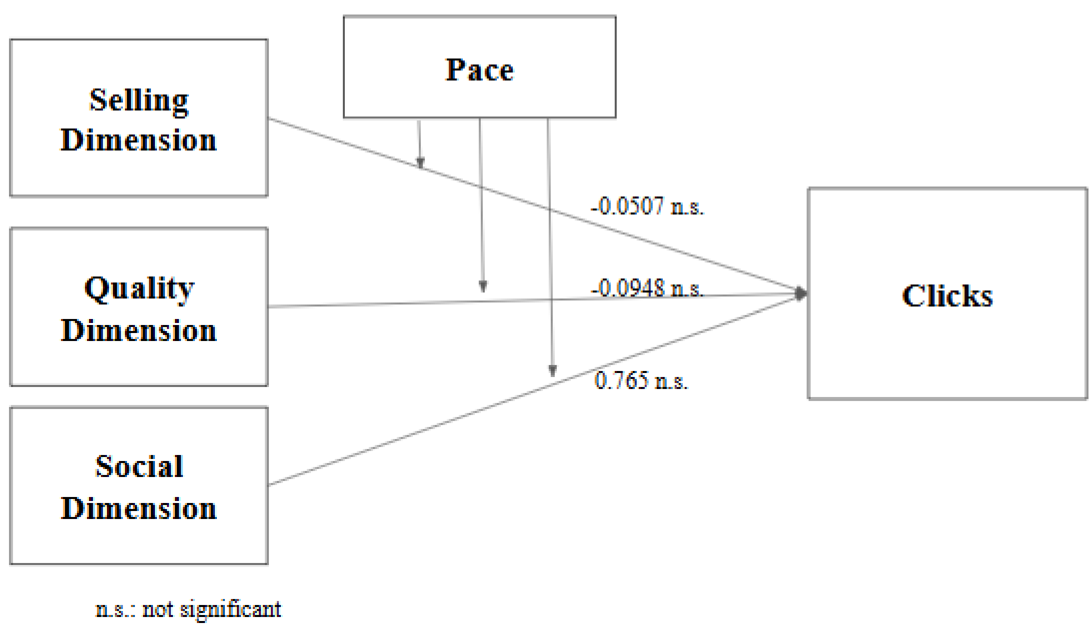
<u>Figure 15: Results of multiple linear regression with content and clicks - at end</u>



It is worth noting that the start and end models using *sustained views* as the dependent variable, β in *selling* and β in *quality* are negative, while with *clicks*, they are positive. With *sustained views*, at the start of the video, *quality*'s negative association is significant (β= -0.181, p-value = 0.04) and, at the end of the video, there is a significant negative association of *selling* (β= -0.345, p-value = 0.001).

To finalize the comparison, a moderator test using Hayes Process Macro was performed, featuring *pace* as an interaction term with each content dimension and *clicks* as the dependent variable, plus the control variable *platforms*. The Results in Appendix 8 show that the interaction terms were not significant. However, the strength of the relation changes when *pace* is a moderator in comparison with the regular model, with an indication, although not significant, that β is negative for *quality* and *selling* and positive for *social*. These results reinforce the need for future studies to investigate *pace* and reach more robust conclusions.

Figure 16: Summary of results of moderation test with clicks



Chapter 4
Discussion

The rich data set provided by the anonymous gaming company, combined with the moment-to-moment qualitative analysis, enabled the investigation to extend beyond the six hypotheses formulated. Consequently, although not initially anticipated, this dissertation yielded distinct statistically significant results using two different dependent variables related to Active and Passive types of Ad Engagement. This section discusses the findings, dividing them into Study 1, which focuses on *sustained views*, the original dependent variable, and Study 2, which highlights the results associated with the variable *clicks*.

4.1 Active & Passive engagement

The environment, which is known for playing a significant role in consumer behaviour (Kotler, 1974), also heavily influenced the present research, particularly in terms of how users interact with advertising on social media platforms, regarding active and passive demonstrations of engagement on Meta apps (Facebook and Instagram). The key finding from this dissertation is that content dimensions have a different impact depending on the desired ad engagement.

Using gaming advertising as the context, this investigation followed the methodology of Nepomuceno et al. (2020), which analyzed video game marketing materials, in the form of social media organic posts, and commercial performance, measured by likes, comments, and shares. The novelty in the present study is the use of advertising data, allowing for the inclusion of a new dependent variable: *sustained views* (rate of complete video views and views of the start), building on the fact that views are a predictor of commercial performance when it comes to video game marketing (Dallo, 2019). *Sustained views*, which can only be collected as aggregated results of advertising campaigns from Meta Business Manager, can be seen as a passive type of engagement (Hemmings-Jarrett et al., 2017; Pagani et al., 2011) since users stop scrolling to watch the ad for a prolonged period.

Initially planned as a control variable, *clicks* were later included as an additional dependent variable after the correlation matrix revealed they had a substantial impact on the model, being associated with five out of seven variables. It's worth noting that one of the reasons it was not initially chosen to be a dependent variable was that Meta Business Manager does not provide the moment at which the click occurred, giving it less relevance for a time-related investigation, based on a qualitative moment-to-moment analysis, when compared to *sustained views*.

Clicks, an active form of engagement (Shahbaznezhad et al., 2022), is based on a metric from Meta Business Manager called "Clicks (All)", which encompasses ad engagements that involve actively clicking on the creative, such as link clicks, shares, comments and reactions (Facebook, 2024). It's more closely related to the dependent variable used in Nepomuceno et al. (2020)'s framework, except it adds link clicks, a result that can only be collected through advertising, representing an aggregated type of data that cannot be associated with a specific user account.

The dichotomy between Active and Passive engagements sheds light on how different consumer behaviours can be associated with content dimensions. Consequently, it reinforces the idea that marketers should place greater emphasis on shaping consumer attitudes to enhance engagement with Facebook ads (Wiese & Sanne, 2018). This fact, although not anticipated with dedicated hypotheses, helps explain why, when commercial performance is *clicks*, findings are so different from *sustained views*.

4.2 Study 1: Sustained views

The passive engagement, *sustained views*, was the original dependent variable and therefore the subject of the six hypotheses. H3 being validated, as shown on Table 13, corroborates findings from another study based on qualitative analysis of long form video game content, which found *social* to be a positive predictor of views (Dallo, 2019) and reinforces investigation around the use of influencer marketing that suggest the addition of human interactions in marketing materials is positively related to consumers' immersion (Jung & Im, 2021). The model also found that *sustained views* are higher on *Facebook* (β= 0.71, p-value = 0.04). One reason for that, according to past research, could be attributed to the finding that users see ads on Instagram, specifically on

Stories, as more intrusive than on the Facebook wall (Belanche et al., 2019), leading to the acceptance of the creatives and, consequently, explaining the longer views on Facebook.

Table 13: Hypothesis validation

Hypothesis	Conclusion	Results
H1. The dimension selling is positively associated with sustained views.	Rejected	β -0.109, p-value 0.181
H2. The dimension quality is positively associated with sustained views.	Rejected	β -0.88, p-value 0.284
H3. The dimension social is positively associated with sustained views.	Validated	β 0.226, p-value 0.006
H4. The presence of pace positively increases the association between selling and sustained views.	Rejected	β -0.019, p-value 0.815
H5. The presence of pace positively increases the association between quality and sustained views.	Rejected	β 0.1291, p-value 0.15
H6. The presence of pace positively increases the association between social and sustained views.	Rejected	β 0.12, p-value 0.878

As the investigation progressed, significant findings emerged regarding the timing of content placement in the videos, as the moment-to-moment analysis allowed for the generation of variables related to four moments of the video (0 to 7.5s, 7.5s to 15s, 15s to 22.5s, and 22.5 to 30s). For this reason, since *sustained views* are a ratio between the end and the start of the creative, it was interesting to look at how the content that appears at the start of the video relates to *sustained views* and apply the same logic to the end of the video. Results show that *social* remains positively and significantly associated with *views* if it appears at both the start and end of the video. This result highlights the importance of this dimension in generating longer views related to the gaming community, corroborating Dallo's (2019) findings on this topic.

Nonetheless, for the other content dimensions, the relationship becomes significant at times, but it goes in the opposite direction from *social*, as shown in Table 14. *Quality*, when added in the first 7.5 seconds of the video, generates a significant negative association (β=-0.193, p-value = 0.02) with *sustained views*. Furthermore, when *selling* appears in the final 7.5 seconds of the videos, it generates a significant negative association (β=-0.354, p-value = 0.001). These results suggest that making the video resemble an advertisement, by incorporating explicit and implicit selling elements, as well as information on how the game is played (gameplay), has a negative impact on passive engagement behaviour. These elements make the creatives look less like native videos – ads that mimic the surrounding content to increase relevance (Wang et al., 2020)– which would, for example, be a video a friend would post on Instagram. Therefore, they break the passive engagement, which is quantified in this research by *sustained views*.

Table 14: Content dimensions' significant Betas vs sustained views

Dependent Variable	Sustained View
Social (full video)	β= 0.226, p-value= 0.006
Social (first 7.5 seconds)	β= 0.170, p-value= 0.04
Social (last 7.5 seconds)	β= 0.164, p-value= 0.03
Quality (first 7.5 seconds)	β= -0.193, p-value= 0.02
Selling (last 7.5 seconds)	β= -0.354, p-value 0.001

The main conclusion drawn from Study 1 is that when ad engagement is passive, the content dimension *social* has an overall positive impact. However, *quality* and *selling* dimensions have a negative impact depending on when they appear. The positive Betas from *social*, indicating social elements are welcomed at the start and end of the video to promote longer engagement, align with findings that propose relationships motivate engagement in SNSs (Nepomuceno et al., 2019). The negative results of *selling* at the final portion of the video could be explained by the fact that viewers understand the content is over and stop watching, as in the analyzed videos, this dimension was often represented with the addition of explicit selling elements (a button call-to-action displaying Download Now or Available Now) in the last seconds. Meanwhile, for *quality*'s negative association during the first seconds of the video, an explanation lies in the fact that marketers must ensure consumers perceive ads as valuable by adding the right amount of informational and entertainment aspects (Ducoffe, 1996), and perhaps the gaming ads could have used more personalized ads or more effective targeting (Wiese et al., 2020) to match the information with the right audience and generate longer engagement.

4.3 Study 2: Clicks on ads

The results, shown on Table 15, allow to conclude that *quality* is a positive predictor of *clicks* (β= 0.280, p-value = 0.002), which go hand in hand with other literature that suggests that increasing quality perception leads to elevated purchase intentions (Moldovan et al., 2019) and that ads containing information cues are positively associated with contributing to the perception of social media advertising value (Arora & Agarwal, 2019). As done with *sustained views*, a start and an end analysis were included, and they show that the decrease in the association strength between *quality* and *clicks* as the video progresses is also notable (β goes from 0.325 to 0.287), suggesting this content has a higher impact on an active behaviour at the beginning of the video advertising.

Similarly, *selling* content dimension serves as a significant positive predictor (β = 0.194, p-value = 0.02), which confirms other studies that have found that adding selling elements influences business performance (Culnan et al., 2010). Nevertheless, the strength of the association with *clicks* is positive but borderline significant when selling elements are placed at the start (β= 0.163, p-value = 0.054), and significant (β= 0.202, p-value = 0.03) at the end of the video.

Table 15: Content dimensions' significant Betas vs clicks

Dependent Variable	**Click Rate**
Selling (full video)	β= 0.194, p-value= 0.02
Selling (last 7.5 seconds)	β= 0.202, p-value= 0.03
Quality (full video)	β= 0.280, p-value= 0.002
Quality (first 7.5 seconds)	β= 0.325, p-value=0.001
Quality (last 7.5 seconds)	β= 0.287, p-value=0.003

Social's association with clicks is not statistically significant, and no conclusions can be drawn at this time. Opposite to *sustained views*, social did not yield significant results in the overall model, nor in the start and finish analyses.

The conclusion of study 2 is that quality and selling elements have an overall positive impact on active ad engagement. *Quality*, although having a positive effect on both start and finish, is stronger on the dependent variable, *clicks*, at the beginning of the video advertising. Whereas, with *selling*, results show that this dimension is stronger when shown at the end of the video than at the start.

These results indicate, moreover, that *selling*'s positive association at the final portion of the video means users understand the presence of selling elements, prompting them to click. As mentioned earlier, in the analyzed videos, this dimension was often represented by the addition of explicit selling elements in the form of a call-to-action button (Download Now, Available Now), in the final seconds of the ads.

On *quality*, the finding is in line with results from other studies interested in clicks and advertising, which concluded that "users are more likely to click on Facebook-based advertising if they perceive it as informative, rather than irritating" (Kim et al., 2016: 657). Therefore, as quality elements strengthen consumer and brand identification (Nepomuceno et al., 2020), this study demonstrates that this dimension prompts users to actively click rather than passively watch the video.

Furthermore, to summarize the key findings from this dissertation, content dimensions have a different impact depending on the ad engagement, with *quality* and *selling* having a positive impact on Active Ad Engagement, and *social* having a positive impact on Passive Ad Engagement.

Conclusion

This dissertation explores the impact of content on social media gaming ads, primarily testing how content related to *selling, quality*, and *social* can be leveraged to boost ad engagement, specifically *sustained views* or *clicks*, through a combination of qualitative moment-to-moment analysis and historical advertising data from an anonymous video game company. It also delivers managerial recommendations for the most effective mix of content dimensions for attracting potential users to video games, depending on the desired response: passive or active ad engagement. Finally, the analysis method is now validated for use across other games within the company and the broader gaming industry.

Theoretical implications

This study contributes to Marketing Literature by demonstrating that content dimensions have varying impacts based on ad engagement. Active displays of engagement, such as link clicks, likes, comments, and shares, were positive and statistically significantly associated with *selling* and *quality* dimensions in the context of video game advertising on Meta. When the engagement is prolonged and passive (Pagani et al., 2011), as it is with the dependent variable *sustained views*, meaning users remained for an extended period with the video creative, *social* is the content dimension positively associated, while *selling* and *quality* were found to be negative predictors depending on the moment they were included in the 30 seconds creatives (*quality* at start of the video and *selling* at the end of the video).

Another relevant contribution of this dissertation is the methodological framework. Using different dependent variables, this study took inspiration from Nepomuceno et al. (2020)'s field-to-theory framework for organic social media gaming posts. Now, a validated methodological approach is also available in the social media advertising context for video games. Other studies can continue to reflect on this type of methodology, reusing it in other industries or, again, proposing a new dependent variable. Moreover, games within the undisclosed gaming company and among the industry can also leverage a moment-to-moment analysis (Baumgartner et al., 1997) based on past advertising data to determine the optimal mix of content to drive consumer action.

Managerial implications

From a marketing professional's perspective, this dissertation helps managers by highlighting the two different content strategy approaches they can perform depending on the desired type of engagement: passive (views) or active (clicks). This is important because when creating a campaign on Meta Business Manager, media buyers are required to choose a campaign objective, which is associated with the stages of the marketing funnel. Building from the AIDA framework (Attention, Interest, Desire, Action) (Abdelkader et al., 2019), the marketing funnel is traditionally composed of awareness, consideration, and conversion (Colicev et al., 2019) and, as stated in the Introduction chapter, on Meta Business Manager, these stages are part of the options to choose from during campaign creation and they will ultimately guide the optimization of ad campaigns (Facebook, 2025).

One of Facebook's campaign objectives, awareness, has been shown to strongly correlate with the likelihood of leading potential consumers down the marketing funnel and considering a product (Laurent et al., 1995), as well as reducing recall of advertisements from competing brands (Alba & Chattopadhyay, 1986). Therefore, when the desired outcome is to communicate that the brand exists and carve out a space in consumers' minds (Sharp, 2010), marketers should ensure that potential customers spend time with their advertising to process it. One way to measure this is to use sustained views among the Key Performance Indicators (KPIs) because it allows marketers to understand which creatives are generating the highest prolonged exposure.

According to this research's findings, the first managerial recommendation is that creatives should contain social elements to have a positive impact on sustained views on Meta. They can achieve this by incorporating conversational types of interactions within the video, such as adding a human face through influencer marketing (Lou & Yuan, 2019) and using emojis or texts that entice the social media user to keep watching. Ultimately, these stylistic choices, which are heavy on entertaining aspects, as Ducoffe & Curlo (2000) have previously advocated for, and could be considered ads that feature creativity elements (Moldovan et al., 2019), not only information, could help generate passive engagement.

A second recommendation for management would be to keep the creatives light or exclude selling and gameplay elements if the goal is to have social media users spend more time with the creative on Meta, thereby moving them from an awareness to a consideration stage. The results obtained with this research indicate that making the video look more like a gaming ad by including call-to-action and gameplay elements and less like a native video - ads that mimic the surrounding content to increase relevance (Wang et al., 2020) - break the passive ad engagement effect, since adding *selling* at the end and *quality* at the start of the video generated a significant negative impact on sustained views.

Consideration, located in the mid-funnel stage (Abdelkader et al., 2019), is used to move users closer to a conversion. On Facebook (2025), consideration optimization signals to the algorithm that it should find users who are likely to engage with the ad by performing an action, such as clicking on a link, making clicks (metric Clicks (All) on Meta's Business Manager) a relevant KPI.

With the above in mind, a third recommendation is that creatives should contain selling elements to have a positive impact on clicks (which encompasses comments, shares, likes, and link clicks) within Meta, according to findings in this research. Marketers can achieve this by incorporating brand identifiers (part of the implicit selling elements) to generate recognition and influence purchase intentions (Culnan et al., 2010). Therefore, making an ad distinct becomes a big goal to bridge the gap between a brand and the consumer's memory (Nelson-Field, 2010), which will help when they are ready for the purchase stage.

Likewise, a fourth recommendation is that creatives should also contain quality elements to have a positive impact on Active Engagement on Meta. Gameplay elements (part of the *quality* dimension) are pieces of information about the game that will create value for the right consumers (Hamari & Sjöblom, 2017) and help them move closer to the lower funnel, with past research associating high informativeness levels with clicking to forward content (Moldovan et al., 2019) and a good way to evaluate the effectiveness of web ads (Nihel, 2013).

Limits of the study

Although this research yielded valuable findings, it also had its share of limitations. The first one was confirmation and reliability bias, since the coder was not blind to the hypothesis. It would have been better if the person performing the moment-to-moment analysis were unaware of the investigation to avoid bias. Additionally, with only one coder, it was not possible to perform a reliability test (Dallo, 2019) to compare the qualitative analysis from different perspectives. Unfortunately, the gaming company that provided the dataset for this study only allowed one person to have access to the sensitive data.

Secondly, the length of videos is a factor that limits the study. Because in the methodology, it was decided that the dependent variable was a sustained view rate (number of completed views divided by the number of views at the 25% level of the video), the exclusion of videos with 15 seconds was needed to keep the ads the same length and avoid biasing the results. This resulted in a reduction in the sample size of analyzed videos, which, although sufficient to yield valid results, could have been larger (Zeph et al., 2024).

Additionally, the anonymous gaming company did not provide advertising data on conversions from the ads and ad investment, which prevented the methodological framework from utilizing low-funnel metrics (Abdelkader et al., 2019) related to game downloads. Access to more advertising-related metrics could have enriched the study.

The use of a real video game in this research enhances the robustness of the results, particularly because many studies rely on methodologies utilizing fictional brands (Yıldız & Sever, 2021). However, the analyzed sample was limited to only one product from the gaming company, which has several active games being advertised. It could have been valuable to test more games to validate the findings. Lastly, the content of the videos was also a limitation. In some cases, the videos were small iterations, such as a change in the car's colour, for example. Therefore, some of these iterations were excluded from the dataset to prioritize the different types of content and create a richer dataset in terms of content. However, a more exhaustive analysis (Dallo, 2019), incorporating additional videos, could have helped address some of the uncertainties of this study.

Future research

Given that statistically significant results were obtained, the marketing literature can continue to explore the relationship between content dimensions and ad engagement, either passive or active. Among future investigations prompted by the current dissertation, two could be prioritized using the same anonymous gaming company, and others could be directed at the marketing field in general.

First and foremost, it would be valuable to replicate this research with other games from the same company to provide a richer data sample (Malthouse & Li, 2017) and ultimately reach more robust findings related to the present dissertation. Some of the hypotheses could not be validated due to non-significant results, which could be attributed to many factors, including the number of videos analyzed and the content of the videos. Using a single racing video game does not allow for universal results, and therefore, a follow-up is imperative.

Secondly, if the company allows, there is the possibility of designing a study focused on the bottom of the marketing funnel (Abdelkader et al., 2019), which is more interested in the conversion stage, specifically in terms of game downloads. Investigating how content relates to the actual downloads of this free mobile game, used as the dependent variable of ad engagement in a third study, could be helpful to compare with the results found using clicks since not necessarily they translate into a buying behaviour (Nihel, 2013), This third study would generate more learnings on how the whole marketing funnel works, from awareness to conversions.

In the marketing field in general, future research could also explore the same methodology but with other popular social media platforms, such as YouTube, TikTok, and Snapchat, as well as a more in-depth investigation of demographics by investigating differences among active and passive interactions with the ads when the users are female and male gamers, as literature indicates marketers in the gaming industry should also be careful when crafting messages to diverse markets (Tourangeau, 2022).

Additionally, there is a line of investigation worth exploring regarding public and private forms of engagement among the dependent variables that could be utilized in a future study. Within the variable *clicks*, there were forms of public engagement, such as likes, comments, and shares, which allows anyone on Facebook or Instagram to see the account associated with the action, leading to a deliberate public behaviour (Yoon et al., 2018). Nevertheless, there was also a form of private engagement: link clicks. Only the advertiser knows how many people clicked on the call-to-action button, and this information is displayed on Meta Business Manager as an aggregated number. As a result, there is no way to associate a Facebook or Instagram account with a visit to the website, for example. This dichotomy could lead to interesting differences or reinforce the findings of this research when it comes to the prediction of content dimensions associated with social media users that tend to share content online (Moldovan et al., 2019), having a more public type of behaviour.

Finally, even though the study surrounding the message was found to be significant, the inclusion of the ad design element *pace* did not yield the expected results. When used as a moderator in this dissertation, *pace* was not found to have a significant positive impact on *sustained views*. However, there is still room to explore this variable in future studies, as other research has found that advertising involves levels of attention (Geng et al., 2021). Furthermore, the idea behind including quicker cuts is to thoughtfully prompt users to process information rapidly (Jin, 2016). Therefore, further investigation would enable a more accurate conclusion regarding the use of this ad design choice.

In conclusion, this research has shed light on the effectiveness of advertising strategies within the gaming industry, particularly the role of content dimensions in shaping social media users' attitudes toward ads. The findings suggest that *social* elements are crucial factors in building longer passive exposure and that *selling* and *quality* elements help drive active engagement toward an ad. There is also valuable insight for academia aiming to enhance ad engagement, depending on whether the outcome is active or passive engagement. While this study focused on a specific video game, it could benefit from being replicated with other games and from requesting the inclusion of low-funnel metrics, such as game installs associated with the ads. As digital advertising continues to evolve, content marketing strategies are crucial for brands to capture consumers’ attention, and the current methodology highlights practical ways to engage with audiences.

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Appendices

APPENDIX 1

Results of Multiple Linear Regression with Content Dimensions.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.422(a)	.178	.164	.91413982
2	.501(b)	.251	.219	.88389320

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social), Zscore(Selling), Zscore(Quality).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	21.722	2	10.861	12.997	<.001 (b)
2. Regression	30.592	5	6.118	7.831	<.001 (c)

a. Dependent Variable: Zscore(Sustained_View)
b. Predictors: Constant, Zscore(FB rate), IG_rate.
c. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social), Zscore(Selling), Zscore(Quality).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	-.690	.804		-.858	.393
	Zscore(FB_rate)	.714	.356	.714	2.008	.047
	IG_rate	1.178	1.365	.307	.863	.390
2	Constant	-.678	.778		-.871	.385
	Zscore(FB_rate)	.711	.344	.711	2.068	.041
	IG_rate	1.158	1.321	.301	-.876	.383
	Z Selling	-.109	.081	-.109	-1.347	.181
	Z Quality	-.088	.082	-.088	-1.077	.284
	Z Social	0.226	.081	.226	2.776	.006

a. Dependent Variable: Zscore(Sustained_View)

APPENDIX 2

Results of Multiple Linear Regression with Content Dimensions - at start.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.422(a)	.178	.164	.91413982
2	.514(b)	.264	.232	.87618974

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_7), Zscore(Selling_7), Zscore(Quality_7).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	21.722	2	10.861	12.997	<.001 (b)
2. Regression	32.178	5	6.436	8.383	<.001 (c)

a. Dependent Variable: Zscore(Sustained_View)
b. Predictors: Constant, Zscore(FB rate), IG_rate.
c. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_7), Zscore(Selling_7), Zscore(Quality_7).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	-.690	.804		-.858	.393
	Zscore(FB_rate)	.714	.356	.714	2.008	.047
	IG_rate	1.178	1.365	.307	.863	.390
2	Constant	-.699	.772		-.905	.368
	Zscore(FB_rate)	.698	.342	.698	2.039	.044
	IG_rate	1.193	1.312	.311	.909	.365
	Z Selling_7	.024	.080	.024	.299	.766
	Z Quality_7	-.193	.084	-.193	-2.310	.023
	Z Social_7	0.170	.083	.170	2.034	.044

Dependent Variable: Zscore(Sustained_View)

APPENDIX 3

Results of Multiple Linear Regression with Content Dimensions - at end.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.422(a)	.178	.164	.91413982
2	.555(b)	.308	.278	.84958770

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_22), Zscore(Selling_22), Zscore(Quality_22).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	21.722	2	10.861	12.997	<.001 (b)
2. Regression	37.549	5	7.510	10.404	<.001 (c)

c. Dependent Variable: Zscore(Sustained_View)
d. Predictors: Constant, Zscore(FB rate), IG_rate.
e. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_22), Zscore(Selling_22), Zscore(Quality_22).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	-.690	.804		-.858	.393
	Zscore(FB_rate)	.714	.356	.714	2.008	.047
	IG_rate	1.178	1.365	.307	.863	.390
2	Constant	-.791	.749		-1.057	.293
	Zscore(FB_rate)	.783	.331	.783	2.364	.020
	IG_rate	1.351	1.272	.352	1.062	.290
	Z Social_22	.164	.078	.164	2.116	.036
	Z Selling_22	-.354	.083	-.354	-4.272	<.001
	Z Quality_22	-0.107	.083	-.107	-1.299	.197

Dependent Variable: Zscore(Sustained_View)

APPENDIX 4

Moderation Test with Selling x Pace (Dependent Variable: Zscore (Sustained_View))

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.4361	.1902	.8444	5.4959	5.0000	117.0000	.0001

	coeff	se	t	p	LLCI	ULCI
Constant	.0011	.0830	.0134	.9894	-.1633	.1655
Selling	-.0924	.0844	-1.0948	.2759	-.2597	.0748
Pace	.0652	.0843	.7732	.4410	-.1018	.2321
Int_1	-.0195	.0830	-.2344	.8151	-.1839	.1450
IG_rate	.2589	.3607	.7177	.4744	-.4555	.9732
FB_rate	.6849	.3597	1.9041	.0594	-.0275	1.3973

Moderation Test with Quality x Pace (Dependent Variable: Zscore (Sustained_View))

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.4566	.2085	.8254	6.1629	5.0000	117.0000	.0000

	coeff	se	t	p	LLCI	ULCI
Constant	.0101	.0822	.1225	.9027	-.1528	.1729
Quality	-.0912	.0845	-1.0792	.2827	-.2586	.0762
Pace	.0519	.0835	.6223	.5349	-.1134	.2173
Int_1	.1291	.0900	1.4347	.1540	-.0491	.3073
IG_rate	.3358	.3577	.9386	.3499	-.3727	1.0443
FB_rate	.7222	.3560	2.0288	.0448	.0172	1.4272

Moderation Test with Interaction Social x Pace Dependent Variable: Zscore (Sustained_View)

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.4857	.2359	.7967	7.2247	5.0000	117.0000	.0000

	coeff	se	t	p	LLCI	ULCI
Constant	.0000	.0805	-.0005	.9996	-.1594	.1594
Social	.2340	.0810	2.8907	.0046	0.737	.3944
Pace	.0569	.0817	.6967	.4874	-.1048	.2186
Int_1	.0126	.0828	.1526	.8789	-.1514	.1767
IG_rate	.2690	.3523	.7637	.4466	-.4287	.9668
FB_rate	.6739	.3510	1.9198	.0573	-.0213	1.3690

APPENDIX 5

Results of Multiple Linear Regression with Content Dimensions and Clicks

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.062(a)	.004	-.013	1.00633280
2	.365(b)	.133	.096	.95085470

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social), Zscore(Selling), Zscore(Quality).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	.475	2	.238	.235	<.791 (b)
2. Regression	16.217	5	3.243	3.587	<.005 (c)

a. Dependent Variable: Zscore(Click rate)
b. Predictors: Constant, Zscore(FB rate), IG_rate.
c. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social), Zscore(Selling), Zscore(Quality).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	.075	.885		.085	.932
	Zscore(FB_rate)	-.095	.392	-.095	-.241	.810
	IG_rate	-.129	1.503	-.034	-.086	.932
2	Constant	.086	.837		.103	.918
	Zscore(FB_rate)	-.105	.370	-.105	-.284	.777
	IG_rate	-.147	1.421	-.038	-.103	.918
	Z Selling	.194	.087	.194	2.221	.028
	Z Quality	.280	.088	.280	3.192	.002
	Z Social	-.114	.088	-.114	-1.299	.197

a. Dependent Variable: Zscore(Click rate)

APPENDIX 6

Results of Multiple Linear Regression with Content Dimensions and Clicks at start

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.062(a)	.004	-.013	1.00633280
2	.426(b)	.182	.147	.92364215

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_7), Zscore(Selling_7), Zscore(Quality_7).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	.475	2	.238	.235	<.791 (b)
2. Regression	22.186	5	4.437	5.201	<.001 (c)

a. Dependent Variable: Zscore(Click rate)
b. Predictors: Constant, Zscore(FB rate), IG_rate.
c. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_7), Zscore(Selling_7), Zscore(Quality_7).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	.075	.885		.085	.932
	Zscore(FB_rate)	-.095	.392	-.095	-.241	.810
	IG_rate	-.129	1.503	-.034	-.086	.932
2	Constant	-.044	.814		-.054	.957
	Zscore(FB_rate)	-.026	.361	-.026	-.071	.944
	IG_rate	.075	1.383	.019	.054	.957
	Z Social_7	-.130	.088	-.130	-1.481	.141
	Z Selling_7	.163	.084	.163	1.944	.054
	Z Quality_7	.325	.088	.325	3.685	<.001

a. Dependent Variable: Zscore(Click rate)

APPENDIX 7

Results of Multiple Linear Regression with Content Dimensions and Clicks at end.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the estimation
1	.062(a)	.004	-.013	1.00633280
2	.300(b)	.090	.051	.97414603

a. Predictors: Constant, Zscore(FB rate), IG_rate.
b. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_22), Zscore(Selling_22), Zscore(Quality_22).

Anova (a)

Model	Sum of squares	df	Mean Square	F	Sig.
1. Regression	.475	2	.238	.235	<.791 (b)
2. Regression	10.972	5	2.194	2.312	<.048 (c)

a. Dependent Variable: Zscore(Click rate)
b. Predictors: Constant, Zscore(FB rate), IG_rate.
c. Predictors: Constant, Zscore(FB rate), IG_rate, Zscore(social_22), Zscore(Selling_22), Zscore(Quality_22).

Coefficients (a)

	Model	B	Std. Error	Standard Coefficient Beta	t	Sig.
1	Constant	.075	.885		.085	.932
	Zscore(FB_rate)	-.095	.392	-.095	-.241	.810
	IG_rate	-.129	1.503	-.034	-.086	.932
2	Constant	.211	.858		.246	.806
	Zscore(FB_rate)	-.151	.380	-.151	-.397	.692
	IG_rate	-.361	1.458	-.094	-.248	.805
	Z Social_22	-.097	.089	-.097	-1.088	.279
	Z Selling_22	.202	.095	.202	2.127	.035
	Z Quality_22	.287	.095	.287	3.029	.003

a. Dependent Variable: Zscore(Click rate)

APPENDIX 8

Moderation Test with Selling x Pace (Dependent Variable: Zscore (Clicks))

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.3827	.1464	.8900	4.0144	5.0000	117.0000	.0021

	coeff	se	t	p	LLCI	ULCI
Constant	.0029	.0852	.0339	.9730	-.1659	.1716
Selling	.1958	.0867	2.2592	.0257	.0257	.3675
Pace	-.3379	.0865	-3.9046	.0002	-.5093	-.1665
Int_1	-.0507	.0853	-.5951	.5529	-.2196	.1181
IG_rate	.1683	.3703	.4545	.6503	-.5651	.9017
FB_rate	.0486	.3693	.1316	.8955	-.6828	.7800

Moderation Test with Quality x Pace (Dependent Variable: Zscore (Clicks))

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.4271	.1824	.8525	5.2204	5.0000	117.0000	.0002

	coeff	se	t	p	LLCI	ULCI
Constant	-.0074	.0836	-.0886	.9296	-.1729	.1581
Quality	.2434	.0859	2.8343	.0054	.0733	.4135
Pace	-.3051	.0848	-3.5970	.0005	-.4732	-.1371
Int_1	-.0948	.0914	-1.0370	.3019	-.2759	.0863
IG_rate	.0710	.3636	.1952	.8456	-.6491	.7910
FB_rate	.0155	.3618	.0427	.9660	-.7011	.7320

Moderation Test with Interaction Social x Pace Dependent Variable: Zscore (Clicks)

Model Summary	R	R-sq	MSE	F	df1	df2	p
	.3668	.1346	.9024	3.6380	5.0000	117.0000	.0043

	coeff	se	t	p	LLCI	ULCI
Constant	-.0002	.0857	-.0028	.9978	-.1699	.1694
Social	-.1431	.0862	-1.6606	.0995	-.3137	.0276
Pace	-.3231	.0869	-3.7178	.0003	-.4952	-.1510
Int_1	.0765	.0881	.8684	.3870	-.0980	.2511
IG_rate	.1053	.3749	.2810	.7792	-.6372	.8479
FB_rate	.0271	.3736	.0725	.9424	-.7128	.7669